OPTIMAL STRATEGIES FOR DEMAND CHARGE REDUCTION BY COMMERCIAL BUILDING OWNERS

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OPTIMAL STRATEGIES FOR DEMAND CHARGE REDUCTION BY COMMERCIAL BUILDING OWNERS

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To my beloved parents

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LIST OF SYMBOLS AND ABBREVIATIONS

kW	kilowatt
kWh	kilowatt hours
DR	demand response
DPEC-3	demand plus energy credit-3
DRP	demand reduction period
PG&E	Pacific gas & electricity
PDP	peak day pricing
TOU	time-of-use
HVAC	heating, ventilation, and air conditioning
GP	Georgia power
PL	power & light
PLM	Power and Lighting Medium
SCE	Southern California Edison
PV	photovoltaic
CPP	critical peak pricing
SA	sensitivity analysis
DER	distributed energy resource
UQ	uncertainty quantification
MW	megawatt
DIY	do it yourself
SHGC	solar heat gain coefficient
ECCR	environmental compliance cost recovery

NCCR	nuclear construction cost recovery
FCR	fuel cost recovery
MFF	municipal franchise fees
HUD	hours use of demand
EEM	energy efficiency measure
EFM	energy flexibility measure
DOE	Department of Energy
DWR	department of water resources
TMY	typical meteorological year
NPV	net present value
GURA-W	Georgia Tech uncertainty and risk analysis workbench
CVRMSE	Coefficient of variation of the root mean square error

SUMMARY

A substantial part of electricity bills in various types of commercial buildings, such as office buildings, hospitals and retails can consist of demand charges. Demand charges represent the penalty for an electricity consumer levied by the utility provider. They are typically a direct result of the shape of the power duration curve, in particular, the hours that a certain power level is exceeded in a given billing period (normally a month). Lowering the peak and/or reducing the hours that a power threshold is exceeded can drastically reduce demand charges. The ability to do so by dynamic, operational adjustments reflects the "energy flexibility" of the building. This term is now widely used in Europe and is the subject of a new international effort (IEA Annex 67) in this area.

This thesis targets the optimal choice among design and operational measures in a retrofit or new design project that delivers the most effective way of reducing demand charges and increasing energy flexibility of commercial buildings. This goal will be achieved through an analysis of all feasible energy and peak reduction measures in different building types and in different use contexts. A search algorithm that compares all possible interventions will deliver the optimum, first with a deterministic analysis then with the recognition of the effects of all possible sources of uncertainty. This thesis evaluates the measures that are commonly adopted to decrease energy consumption and increase energy flexibility and thus reduce demand charges, including (1) upgrading building components and installing energy efficient equipment; (2) applying dynamic building load control strategies such as demand-side management; (3) installing a rooftop photovoltaic (PV) panel array. Operational interventions include the manipulation of thermostat settings and possibly the voltage reduction of lighting and appliances (in some cases including

HVAC components) in the building, which may reduce thermal and visual comfort for certain periods. In order to support retrofit and design improvement decisions, an approach is developed that finds the optimal mix of measures that maximize the net present value of the investment in energy flexibility measures over twenty years for the owner.

This study will analyze optimal solutions for three commercial building types. Differences between them in terms of energy use and peak demand will be investigated and a generically applicable measure of energy flexibility will be developed. These three buildings are chosen (by scaling their total floor area) such that their demand charges are in the same range. The monetary benefit of energy flexibility will be studied under different demand charge rate structures and under variable building consumption scenarios. This research will result in a new optimization framework for choosing the optimum among multiple options. Based on the proposed framework, this research will determine optimal ways to increase energy flexibility, leading to the best investment decisions for different commercial building types in different locations and under different rate structures.

CHAPTER 1 INTRODUCTION

1.1 Importance of Demand Charges

Most owners of commercial buildings may not realize that demand charges can easily make up 70% of their buildings' monthly utility bills (Dieziger 2000). Demand charges represent the penalty levied by the utility provider for an electricity user, particularly for big electricity consumers in the power grid. Demand charges are typically a direct result of the shape of the power duration curve of the building, in particular, the hours that a certain power level is exceeded in a given billing period. According to the recently published data from the survey of EIA in 2016 (EIA 2016), the growth of floor space inside commercial buildings has been twice as fast as the growth of commercial buildings since 2003, which implies a trend of increased occupancy, number of equipment, and area of conditioned space inside average commercial buildings. As a direct result, the electricity usage of new commercial buildings such as office, hospital, retail buildings may keep increasing as a result of size, despite the improved energy efficiency of new buildings. With increased peak power, a growing number of commercial building owners may face the problem of paying far more than what they actually consume due to their increased share in the cost of the grid infrastructure. This share is billed in the form of demand charges. Therefore, it becomes significant for commercial building owners and operators to realize the role of these demand charges in their monthly bills and to take effective measures to reduce them.

Under current utility rate structures, demand charges can easily make up 70% of the monthly utility bill of a commercial building. According to the statistical data for the year 2016, PSE&G's Demand Peak Load Contribution charge is $64.65/kW/yr. JCPL's Demand Peak Load Contribution charge is $43.33/kW/yr (Adjangba 2015). These numbers show the significance of what costs can be mitigated if building owners and their energy advisors are able to understand the core causes of demand charges and take action.

In the process of establishing the power distribution network, most capital funding is allocated for the construction of hardware infrastructure, such as transformers, relays, and cables, etc. The larger size of transformers and cables induce greater cost. Therefore, the most expensive part in constructing the power grid is not to meet the estimated average total electricity demand but to deliver the needed capacity and to guarantee the stability of the power grid. In order to maintain the stability of the power grid, the capacity of the grid need to meet peak demand even during the most severe usage periods. Failing to meet this capacity requirement may lead to blackouts and even threaten public safety on a large scale, such as during the Chicago blackout in 1995, the California power outage in 2000, and the blackout that occurred in 2013 in the New York City (PSOTF 2017). Power outages occur usually as a result of local weather events, usually as the result of high winds, downed trees, and power lines. Large scale power grid failures, such as brown-outs and incidental black-outs, typically occur during an extended heat wave when the peak electricity usage exceeds the capacity of the power grid. These temporary power spikes are the main reason for otherwise inefficient investments in the construction of the power grid. However, these costly investments are necessitated by the fact that the distribution network needs to be capable of handling the peak demand throughout a year. For example, if a factory only has one day of high-intensity operation during the whole year, the power grid still needs to offer the appropriate network capacity to meet this level of demand. Although it is hard to pinpoint the extra investment necessitated by a single large peak consumer, the general attitude of the utility companies is to charge these consumers a collective penalty, which should be a fair reflection of the investment that utilities spend to serve the peak load during a given time window and in a certain subnet of the grid. Therefore, large commercial buildings are charged an additional amount of demand charges beside the basic cost according to their monthly or seasonal peak electricity usage. The utility decides the threshold and the time window of the peak occurrence based on internal (and for the public mostly hidden) cost-revenue calculations. In one type of policies, the usage of electricity during the identified time window in a given year determines the electricity price a building will pay in the following twelve billing months. Since the power grid's transmission and distribution systems are sized for the maximum load of the customers using the supply system, the cost driver for providing the transmission and distribution service is the peak demand. In order to better align the cost of operating those systems with a customer's use of the system, a demand charge is applied to the maximum demand that is recorded on the customer's meter during a specified time period (typically a month) and sometimes during a specific time window of every day.

There are two types of peak demand identifications: the coincident peak demand and the billing demand. Billing demand (or maximum demand) refers to the highest energy demand by the customer in a given billing period. It covers the cost of operation, maintenance, and replacement of the electric distribution system that serves the customer's electricity need. Coincident demand (including on-peak demand and partial-peak demand) is the energy demand required by the electricity customer during a particular time window, which is typically determined as the period that the system-wide electricity demand reaches its peak. These two cases lead to different ways of demand charge calculation. Coincident peak demand charges reflect how much the end user "contributes" to the cost of the power system based on his electricity consumption during the system peak; in contrast, non-coincident peak demand charges impose a customer for his peak consumption, regardless of the time it occurred. A customer's coincident peak demand is usually calculated from meter readings taken at the time when the customer's demand is likely to be the highest. Their non-coincident peak demand would be calculated using several readings taken at different times to determine what their actual peak demand periods may be. A more sophisticated type of meter is required to calculate non-coincident demand, but it doesn't necessarily produce a better result for the utility. An energy provider may care more about demand at a given time when total customer demand is highest than they care about the peak demand of a given customer during other times (non-coincident peak website). In order to save demand charges on electricity bills, the stakeholder needs to have a thorough understanding of how the demand charge rate is designed by their local utility company. It can be based on the customer's maximum demand across all hours of the month (EIA 2017) or on their demand that occurs during the hours of the day when the power system peaks or the distribution system peaks (referred to as 'coincident peak demand'). This thesis will mainly focus on how to reduce non-coincident peak demand due to the limitation of available data sources of actual electricity loads in the power grid. An optimization framework will be developed such that it can also be applied to minimizing coincident peak related charges.

Demand is defined as "the rate at which electric energy is used at any instant or averaged over any designated period of time and is measured in kilowatt (kW)," in EIA's glossary of energy terms (EIA 2017). In reality, the demand kW is measured by the electric meter as the highest average demand in any 15-minute period during the month. This is counted as the amount of electric load required by the customer's electric equipment operating at any given time. Transmission and distribution utilities must have sufficient electric capacities such as properly sized transformers, service wires and conductors to meet customers' kW demand. The demand in kW is recorded for billing the demand charge each month and then reset on the bill cycle date. A customer's 10 kW demand operating for one hour equals 10 kilowatt hours (kWh), which is the cumulative kWh reading on the meter. In order to level out the recovery of the fixed cost of the transmission and distribution system necessary to serve the customer's maximum demand, the grid operator will monitor the peak demand and apply a demand provision to big electricity consumers whose peak demand exceeds the determined threshold in the grid.

Assuming two companies pay the same price for both electricity consumption ($0.437 per kWh) and demand charges ($2.79 per kW). One building runs a 50 megawatt (MW) load continuously for 100 hours, the total cost of electricity is calculated as:

$$\begin{gathered}50(\mathrm{MW}) \times 100(\mathrm{hr}) \times 0.437\ (\$/\mathrm{kWh}) + \ 50(\mathrm{MW}) \times 2.79(\$/\mathrm{kW}) \\ = 358000(\$)\end{gathered} \tag{1.1}$$

The other building runs a 5 MW load for 1,000 hours, the total cost of electricity is calculated as:

$$\begin{gathered}5(\mathrm{MW}) \times 1000(\mathrm{hr}) \times 0.437\ (\$/\mathrm{kWh}) + \ 5(\mathrm{MW}) \times 2.79(\$/\mathrm{kW}) \\ = 232450(\$)\end{gathered} \tag{2.2}$$

For the same amount of total kWh energy used, i.e. at the same consumption level, albeit with different intensities, the building having a flatter usage profile pays less. (This example does not use actual prices.)

Figure 1.1 lists the historical data of electricity usage of the Con Edison service territory. Figure 1.1 tells that a load higher than 13,000 MW) only occurs seven hours in a year and a load higher than 10,000 MW occurs 156 hours in a year. However, the utility supplier needs to spend billions to upgrade the capacity of the power grid to meet those short periods of peak electricity demand, such as burying more copper wires under the ground and installing larger size transformers. In addition to this, it is highly expensive for the utilities to generate the peak power compared to the costs related to generating the average usage. Some power generating stations have a so-called peak power plant, which only runs occasionally when the power demand in the grid reaches a certain level. When that occurs, it pays a much higher price per kWh generation compared to running only the basic power plant that generates a fixed amount of electricity to meet the base load requirement (Masters 2013). Therefore, effectively reducing the demand during peak hours will reduce the costs and benefit the stability of the power grid. In order to control the peak power and thus to save money, utility companies count on facility managers to reduce their building's power peaks by developing cost incentives specifically directed at them. This explains the rationale of the strategy that the utility company implements demand charges to building owners. Reducing peak demand not only helps building owners save money, but also increase the stability of the power grid in the long run.

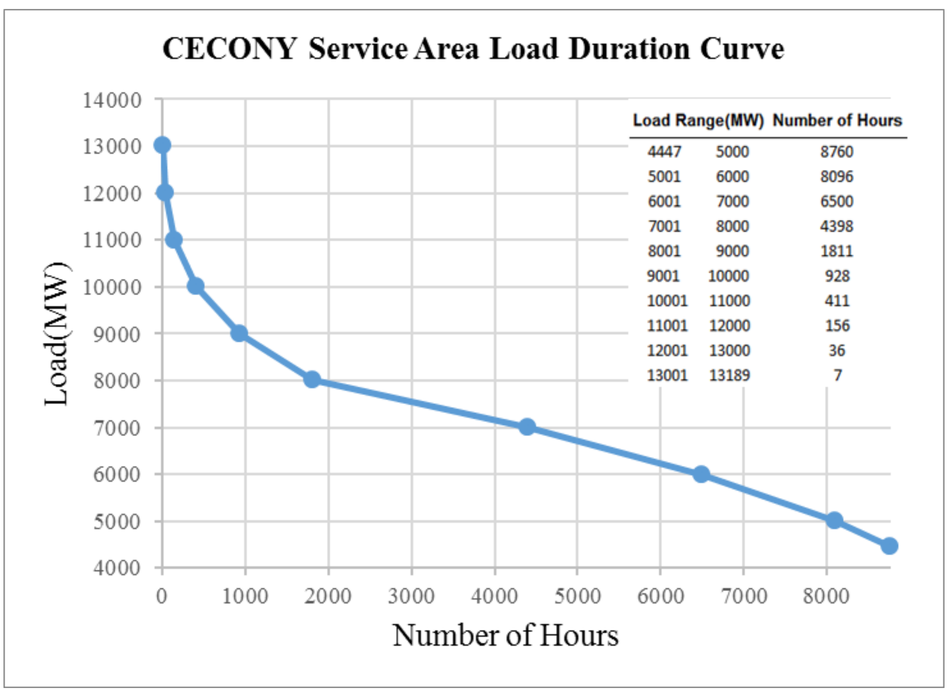


Figure 1.1 Historical data of electricity usage of the Con Edison service territory

1.2 Goals and Hypotheses

This thesis targets an optimization framework that can effectively help utility customers reduce their demand charges with the highest net gain of the investment. An important practical goal of this thesis is that the framework is used to derive one or more customer friendly investment tools. With these, the customer should be able to design an optimal investment package within the constraints posed by the specific building and available budget.

This translates to the following objectives of this thesis:

(1) Evaluate and designate technologies and operations that save on total electricity costs (consumption and demand charges). Eligible technologies and operations will be introduced in section 2.2 in Chapter 2. They are parameterized and differentiated for different building types.

(2) Develop an energy model that captures every eligible technology and operation in a set of model parameters. This model is consequently used to predict total energy costs, given certain rate structures used by a local utility.

(3) Determine generic measures of building energy flexibility and develop a relationship between these measures and demand charge reduction measures in different scenarios and cost settings.

(4) Determine the optimal selection among competing technologies and operational interventions with energy flexibility and optimal cost saving as the target, while obeying performance, technological, and budget constraints.

(5) Repeat step 4 in recognition of uncertainties in physical parameters, usage scenarios, cost models (e.g. damage cost of temporarily deficient thermal comfort), future rates,

deterioration of the performance of certain technologies, etc. This requires the introduction of a stochastic optimization approach driven by customer preference criteria. Rather than employing axiomatic utility theory, this research step is based on a heuristic "robustness" criterion. Defining such a criterion and using it in the optimization is a major intellectual challenge.

(6) Execute step 4 and step 5 in a customer friendly DIY tool.

(7) Validate the reduced order model against a higher fidelity model, such as EnergyPlus (Crawley et al. 2000). This task will focus on verifying whether the comparative analysis that underlies the optimization is supported well enough by EPC. As a measure of validation, the optimal mix found from both approaches will be compared.

This thesis has two major hypotheses:

Hypothesis 1: Customer investment for demand charge reduction has a non-trivial optimum depending on the building type, the rate structure, and other contextual parameters.

Hypothesis 2: In the presence of uncertainties in the savings prediction and cost models, a rational investment decision tool can be based on stochastic optimization.

The practical implication of this thesis is to help commercial building owners reduce demand charges on their utility bills, and thereby indirectly improve the stability of the power grid. A DIY tool is developed that suggests the optimal mix of technologies and strategies to building owners.

1.3 Significance

This study develops a framework that, for the comprehensive set of technologies and strategies, optimizes energy flexibility and resulting utility bill reduction against investment. The framework reflects differences in building types (currently only considered for a fixed building size) and local utility rate structures. This thesis helps commercial building owners explore the full spectrum of measures to achieve flexibility increase and demand charge reduction. The outcomes from this study include flexibility increase and demand charge reduction strategies for three commercial building types: office, hospital, and retail.

Developers, designers, utility companies, and existing building owners will be able to determine measures and interventions that increase energy flexibility as a signal to the utility providers and reduce demand charges for building owners. This will lead to direct financial gains by the different stakeholders, thus indirectly lowering costs for the consumer. This thesis will change people's thinking in the green building industry by emphasizing the importance of instantaneous peak power instead of cumulative energy consumption. This thesis provides a tool to readily find the optimal investment strategy that reduces peak demand and save on building owners' monthly utility bills, thus proliferating the benefit of good energy decisions through the building industry.

1.4 Thesis Structure

Chapter 1 introduces the research background and objective. Chapter 2 contains the concept of energy flexibility, the literature review for different types of demand charges, and the current methods used to reduce demand charges. Chapter 3 presents methods that could effectively reduce the demand charges in commercial buildings and discuss the quantitative analysis model. It will also produce a set of energy flexibility measures (EFMs) and develop its relationship to demand charges. Chapter 4 introduces three different types of commercial building that are considered in this research. It develops the prototype energy models and analyzes the results of the energy efficiency measure (EEM)/EFM optimization studies. Chapter 5 discusses the importance of quantitative analysis of major sources of uncertainty in the predictions and related investment risk. Chapter 6 investigates how stochastic optimization can be used to rationally find the optimum solution. Chapter 7 verifies the reduced order model. Chapter 8 discusses the findings, conclusions of the study, and outline the future work.

CHAPTER 2 DEMAND CHARGES AND ENERGY FLEXIBILITY

2.1 Existing Method to Calculate Demand Charges

Figure 2.1 is a sample bill posted on Pacific Gas & Electricity (PG&E)'s website, which illustrates the decomposition of a typical electricity bill. The electricity bill can be split into three parts. The first part is the monthly or seasonal basic service charge, which is a flat rate that covers the wiring, transmission, and maintenance fee, etc. The second part is the electricity consumption fee, to measure how much energy is consumed in a month. The third part is the demand charge, based on the highest capacity the consumer required during the given billing period, typically a 15-minute interval during that billing cycle. Total energy consumption is like the odometer that records the total mileage of the car, while the peak demand is like the speedometer that captures the speed at the moment and records the maximum value. Consumption is the overall electricity use, while demand is the peak intensity or maximum "speed". All fifty states in the U.S. have demand charges, although the charges vary by state. Demand charges also vary by season, with a generally higher rate in summer than in winter.

Peak demand seldom occurs for more than a few hours or fractions of hours each month or year, but electric companies must maintain sufficient generating and transmission capacity to supply the peak demand. Demand charges reflect high costs that electric companies pay for generating and maintaining transmission capacity that must sit idle for most of the time. Demand charges are based on the amount of energy consumed in a specified period of time known as a demand interval, which is usually 15 or 30 minutes. To calculate a customer's demand, the electric company takes the demand interval with the highest energy consumption in kWh and divides by the length of the demand interval in hours. Mathematically, this is expressed as kWh per hour. The hours cancel, leaving kW as the units of demand. There are a number of ways the peak demand is determined. Different utility companies have different policies regarding the calculation of demand charges in their service regions.

ENERGY STATEMENT
www.pge.com/MyEnergy

Details of Electric Charges

04/09/2013 – 05/08/2013 (30 billing days)
Service For: 1234 Commercial Drive
Service Agreement ID: 9087654321
Rate Schedule: A108 Medium General Demand – Metered Service

04/09/2013 – 04/30/2013				
Customer Charge	22	days	@$4.59959	$101.19
Demand Charge	157.440000	kW	@$5.60000	646.55
Energy Charges	22,168.000000	kWh	@$0.10578	2.344.93
Energy Commission Tax				6.43
Hayward Utility Users' Tax (5.500%)				170.10
05/01/2013 – 05/08/2013				
Customer Charge	8	days	@$4.59959	$36.80
Demand Charge	163.840000	kW	@$12.570000	549.19
Energy Charges	8,372.640000	kWh	@$0.14335	1200.72
Energy Commission Tax				2.43
Hayward Utility Users' Tax (5.500%)				98.24
Total Electric Charges				**$5,156.08**

Figure 2.1 Structure of a monthly electricity bill (example)

The electric schedule A-10 of PG&E (A-10 2017) is designed for customers whose peak demand exceeds 200 kW but less than 499 kW for at least three consecutive months during the most recent 12-month period. Under A-10, customers are charged $16.78 per kW for the summer peak demand and $9.45 per kW for the winter peak demand. Customers will be automatically shifted to the electric schedule E19 if their peak demand exceeds 499 kW but less than 999 kW (E19 2017). This schedule consists of three types of demand charges, a maximum-peak-period demand charge, a maximum-part-peak-period demand charge, and a maximum demand charge. The maximum-peak-period demand charge applies to the peak demand occurred during the month's peak hours. The maximum-part-peak-period demand charge applies to the peak demand occurred during the month's part-peak hours. The maximum demand charge applies to the peak demand occurred any time in the month. The bill includes all the three types. Table 2.1 defines the schedule of on-peak, partial-peak and off-peak hours. Here's an example of how PG&E charges their customers in their monthly electricity bills. Assume that a building's electricity demand is between 499 kW and 999 kW during one summer month, the building will be under plan E19. The demand meter tells that the customer's maximum-peak-period demand is 400 kW, the maximum-part-peak-period demand is 350 kW, and the monthly maximum demand is 650 kW. The total amount of demand charges equals to

$$650\ (kW) \times 17.32(\$/kW) + 400\ (\mathrm{kW}) \times 1.56\ (\$/kW) + 350\ (\mathrm{kW}) \times 0.53\ (\$/kW) = 12067.5(\$) \tag{3.2}$$

When a billing month includes both summer and winter days, PG&E will define the applicable peak demands for the summer and winter portions separately, calculate the demand charge with corresponding charge rate for each portion, and then add them up together proportionally based on the number of summer and winter billing days.

Different from the PG&E's demand charge rate structure, National Grid uses customer's total energy usage to determine whether they should be charged for demand charges. If the total monthly energy usage (kWh) of the end user exceeds a pre-determined level for four consecutive months, the National grid will install a demand meter at the end user's place and start to bill for demand charges. Once demand billing begins, it does not end until after the monthly energy consumption has been less than the pre-determined level for twelve consecutive months. On every demand-billed customer's energy service bill, charges for consumption and demand are separate. According to Demand G-2 schedule, National Grid demand schedule G-2 applies to commercial and industrial customers whose monthly usage is above 10,000 kWh and demand below 200 kW

(Demand G-2 2017). If the total energy usage in a commercial building exceeds the 10,000 kWh, the customer will be charged for demand charges. Here's an example of how demand charges are calculated. Assume the customer's fully installed load is 40 kW. The electricity bill will show the consumption, plus the National Grid's basic service charge of $47.25 per 30-day period, which includes maintenance of gas or electric lines, metering and other costs such as meter reading and billing, the total is $40 \times 0.07 + 47.25 = 50.05$. The meter reading is 40 kW with a demand charge of $8.32 per kW, the demand charge is $40 \times 8.32 = 332.8$. In this case, almost 90% of the electric bill is for demand charges.

Table 2.1 Definition of times of the year and times of the day

Times of the year and times of the day are defined as follows:		
Summer	Period A (Service from May 1 through October 31)	
On-Peak	12:00 P.M. to 6:00 P.M.	Monday through Friday (Except Holidays)
Partial-Peak	8:30 A.M. to 12:00 P.M.	Monday through Friday (Except Holidays)
	6:00 P.M. to 9:30 P.M.	
Off-Peak	9:30 P.M. to 8:30 A.M.	Monday through Friday
	All Day	Saturday, Sunday, and Holidays
Winter	Period B (Service from November 1 through April 30)	
Partial-Peak	8:30 A.M. to 9:30 P.M.	Monday through Friday (Except Holidays)
Off-Peak	9:30 P.M. to 8:30 A.M.	Monday through Friday (Except Holidays)
	All Day	Saturday, Sunday, and Holidays

Some utilities have "ratchet" charges where the billing demand is determined by the demand of both the current month and the previous eleven months (applicable summer and winter months). Most of the commercial, industrial and large residential customers in the service territory of GP select the Power & Light (PL) tariffs, and the billing demand in PL tariffs is calculated as a “ratchet” demand. For the summer months (June-September), the billing demand equals to the highest of 100% of the current month demand, 95% of the applicable summer months peak demand, and 60% of the applicable winter month peak demand (October – May). For the winter months, the billing demand equals to 60% of the current month or other applicable winter month peak demand, or 95% of applicable summer month peak demand, whichever is the highest. Figure 2.2 illustrates the method adopted by GP for calculating the peak billing demand. In Power and Light Medium (PLM, PLM-11 2017), customers whose billing demand exceed 30 kW but less than 500 kW will be charged $8.24 per kW for demand charge.

DETERMINATION OF BILLING DEMAND

WINTER (OCTOBER - MAY)	Using actual kW for current month and previous eleven months, Select greater of: - 60% of current month or other winter month - 95% of summer months
SUMMER (SEPTEMBER - JUNE)	Using actual kW for current month and previous eleven months, Select greater of: - 100% of current month - 95% of summer months - 60% of winter months

Figure 2.2 Determination of Billing Demand in GP PL

The ratchet demand is also widely used by the transmission and distribution utility companies in Texas. Since the companies charge the demand usage based on 80% of the customer’s monthly peak demand, if a commercial customer has a peak demand of 250 kW, which exceeds the 200 kW threshold in just one month, they will still be charged for a minimum demand usage at 80% of 250 kW for the next eleven months. Therefore, it is an important investment decision by the commercial building owners to effectively avoid non-critical usage of electricity during peak hours, and consequently reducing their monthly or seasonal electricity bills.

There are other more complicated forms of demand charges, such as the customer demand charges, where the peak is determined based on a rolling six or twelve months' maximum demand. Many utilities will charge their consumer a TOU rate, which embeds some form of demand charges in the billing method. The most common method, which is studied in this thesis is to simply multiply the monthly peak demand usage (kW) by the demand charge rate ($/kW). The monthly peak demand is the highest average power use in kW during a 15 or 30-minute period each month. The demand charge is then added to the customer charge, energy charge, and any taxes to arrive at the total bill. In light of the fact that different local utility companies have different demand charge rates, this thesis considers the impact of different demand charge rates in the case studies. The optimal investment strategy will be discussed for the case buildings under GP's PLM tariffs (case 1) (PLM-11, 2017), PG&E's schedule A-10 option A and B (case 2 and 3) (A-10, 2017), and Southern California Edison (SCE)'s schedule TOU GS-3 option A and B (case 4 and 5) (TOU-GS-3 2017) .

2.2 Existing Method to Reduce Demand Charges

In general, there are four technical interventions or measures used in the demand profile modification. The first one is energy efficiency, which refers to the techniques that help reduce the net demand during both on-peak and off-peak periods. The second technique is called peak shaving, which indicates reducing the on-peak demand when the demand in the power grid is high. The third method is load shifting, which means altering the demand profile to meet certain performance criteria. The fourth method is renewable energy, which utilizes distributed energy resources (DERs) to coincidently reduce on-peak demand. Figure 2.3 shows the difference between the four techniques that can help customers reduce demand charges. The existing method that falls within these four categories mentioned above can help reduce demand charges.

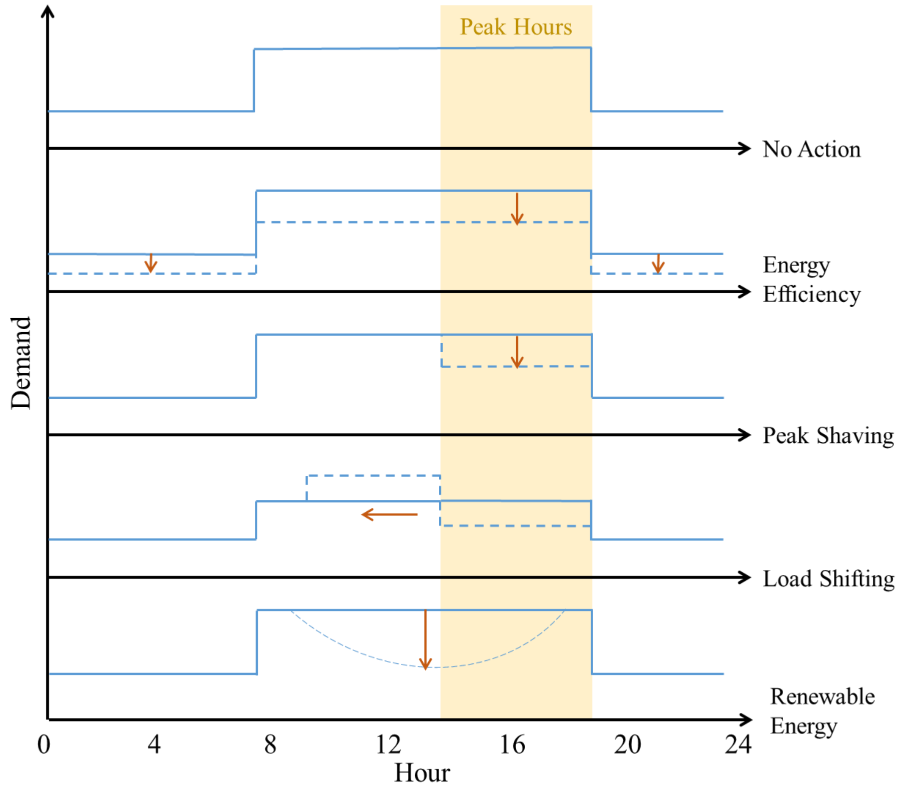


Figure 2.3 Technics to help modify the demand profile

2.2.1 *Energy Efficiency*

Improving energy efficiency in buildings simultaneously reduces power peaks and their duration and reduces the total energy consumption. To improve energy efficiency, the building owner needs to invest in installing energy efficiency features. The following EEMs are considered in this thesis:

1) Improve energy performance of windows to reduce solar radiation through the transparent envelope components during over-heated seasons (i.e. hot summer) as well as increase the insulation of the building by replacing the low-efficiency windows with Low-E windows;

2) Install shading device to reduce solar radiation through the window during hot seasons;

3) Employ white roof and white surfaces on the building skin to reduce solar absorption;

4) Better manage air flows and air leakage of the building;

5) Install insulation materials to improve the thermal performance of the opaque building envelope components.

All measures will be considered at a gliding scale of efficiency, indicating the increase of energy efficiency levels.

2.2.2 Peak Shaving

Peak shaving techniques include dynamic system control strategy such as thermostat adjustment, lighting control, and voltage throttling, etc. While implementing EEMs in a building may reduce the overall electricity load in the building, one important driver of peak demand in commercial buildings is the spike in air conditioning loads during the hot summer afternoon. The facility manager can turn up the thermostat setpoint during these peak hours to reduce the power consumption. Many times, this is done in ways that potentially impact occupant comfort and productivity. We should remember 90% of a business' operating costs is tied up in people and their productivity. Even small effects on productivity can have a significant effect on the bottom line of the investment in a facility. According to a report (WGBC 2014), employee productivity drops by 6% when the temperature exceeds the comfort level threshold. Therefore, while a 10% variation in energy cost might contribute only a small amount to the bottom line for a single building, it can have a disproportionately negative impact on productivity and thus on the businesses total operating cost.

The lighting system is considered to be second biggest energy consumer inside typical office buildings in the U.S. (EIA 2012). Reducing the lighting power intensity by turning off unnecessary lamps and installing lighting dimmers to temporarily reduce the illuminance inside the space during peak hours can effectively reduce the demand of the building, therefore reduce the power usage as well as the peak demand.

2.2.3 Load Shifting

Load shifting techniques refer to measures that could shift eligible loads to lower-cost hours, reshaping the daily load profile. One typical load shifting technique is to turn on the high power consuming equipment in advance or later when the load in the grid is low. For example, the irrigation pump can be used during the night-time. The electric heat boiler can also be turned on in advance to avoid a later power spike.

Another load shifting technique is to utilize the building's thermal mass to pre-cool the building during lower-cost hours. There are two types of thermal mass in a building: the active thermal energy storage and the passive building thermal mass. One practical application of utilizing active thermal energy storage to shift load is the ice storage in the supermarket. The cold storage, which is always turned on to keep the food inside fresh in a supermarket, can take advantage of the cheap electricity at normal or night time to make extra ice and reserve for cooling in daytime keeping the compressor turned off. The setpoint of the cold storage is always too low, which not only is a big energy waste but also makes people feel chili inside. Sometimes, when the setpoint is extremely low, ice can even freeze on the duct, which causes duct aging damage. It can temporally precool and produce some ice during normal hours or night hours and increase the temperature setpoint during peak demand period. Shut down for two hours may have no negative effects with enough precooling.

The passive building thermal mass is in the structure and internal mass of the building. This mass determines how fast the building temperatures react to weather and internal loads especially in periods that the temperature inside is “free floating”, i.e. in between heating and cooling setpoint. The temperature inside the building is usually controlled by the HVAC system at a constant temperature and humidity range to ensure the thermal comfort of the occupants. The thermostat setpoint can be reduced ahead of the peak hours so that the building itself is used as the medium of a thermal storage. That is, the setpoint temperature can be turned down as low as 22℃ as compared to the regular 24 ℃ setting during normal hours. This low temperature may allow the compressor to shut down during the hours of peak power consumption since the building is precooled beforehand. This may be particularly effective if the peak power period is not more than an hour or so, when it may indeed be possible that the thermal storage in the building delays the temperature increase long enough. Thermostats can be set toward the bottom of the comfort zone instead of the top (at 22 ℃ instead of 24℃, for example). The lower temperature before the peak hours allows the air–conditioning compressor to be turned off or its output to be reduced for short periods (peak hours) without raising the temperature that might hinder occupants’ comfort. According to the American Society of Heating, Refrigeration, and Air–Conditioning Engineers, most people will not notice their uncomfortable condition during a one–hour period when a building is hotter than normal. Active pre-cooling of building thermal mass may increase the overall energy consumption, but the additional energy consumed is less expensive compared to the cost of energy that is avoided during peak hours.

When the building is unoccupied, the HVAC is temporarily turned off to let it float to the setpoint that is appropriate for unoccupied periods. The temperature inside the building is then free floating towards that new setpoint. In existing commercial buildings, the structure mass can be utilized as the medium of passive thermal storage to reduce demand charges during a specific period of time. The owner of the commercial building could optimize the control strategy to smooth the daily electricity usage profile and thereby possibly reduce demand charges.

2.2.4 Renewable Energy

Renewable energy sources can help generate energy and reduce purchased electricity from the power grid during peak hours. Installing rooftop PV panel arrays with a battery system is one of the most proliferated technologies to reshape the building load profile.

PV cells can produce electricity during the daytime. A grid-connected PV system can be used as a backup power source. It has two financial benefits: the electric utility bill saving and the power sellback. The power generated by the PV system is used directly on-site and can partially or even completely offset the electricity purchased from the grid, therefore it reshapes the load profile of the end user and saves their electric utility bills. This cost saving benefit of the PV generation is equal to the price of electricity multiplied by the generated power that was used on-site. In power sellback, the generated surplus is sold back to the grid through a sell back meter or in some cases through net metering. Usually, however, the grid operators purchase this sellback electricity at a lower rate compared to the price they charge customers for their usage. During the hot summer afternoon, if there is a higher possibility that the power spike occurs, the PV system can generate electricity for the building's own use and reduce the coincident peak demand of the building.

EDR (2013) and Mount (2004) concluded that energy efficiency, peak shaving techniques are true conservation measures. Load shifting is not considered as a conservation action because it merely shifts the load instead of reducing it. Among the four methods, peak shaving and load shifting are regarded as EFMs, the concept of which will be introduced in the next section.

2.3 Energy Flexibility

The U.S. government plans to invest one trillion in upgrading the conventional grid infrastructure including generation, transmission, and distribution components over the next fifteen years (NARUC 2017). However, the official forecast projects a decreasing trend in the electricity sales during the same period, which implies an increasing retail price of electricity. On the other hand, the DERs, such as the on-site PV panel array, shows an increasing trend in cost-effectiveness. These dual trends and the reaction of building owners could possibly lead to an overinvestment on both sides of the meter under the current business model, which in many regions only allows one-way flow of electricity. The ultimate solution to this problem lies in two aspects: the demand side and the supply side. The demand side could increase the energy flexibility to actively react to the changing power supply conditions, while the supply side could change the current business model to disseminate information and allow the two-way energy flow to be better adapted to the increasing energy flexibility on the demand side. In the power grid, the key factor to maintaining the stability of the electrical power flow is the building owners' ability to flexibly adjust their electricity usage time and patterns. Because demand charges are mainly caused by efforts of the power supply side trying to balance the flip side of the load in the grid, the concept of energy flexibility is very important in the context of the study of demand charge reduction.

Large scale EFMs include grid extension, varied sizes of power generation plants, and converting surplus electricity power to other forms of energy such as thermal, hydrogen, gas. At the building scale, there are four EFMs: (1) dynamic control strategies in building operational system, such as thermostat adjustment, lighting control, and voltage throttling; (2) load shifting of the high power consuming equipment in advance or later when the load on the grid is low; (3) active or passive thermal mass storages and battery storages; (4) onsite renewable generation. It should be noted that in this research the renewable generation is a part of the EFM, instead of the EEM. One of the reasons for this choice is that EFM comprises all measures that can be applied to a building with purely operational interventions. Although the installation of renewable generation is not typically regarded as an operational intervention, it is regarded as such in this thesis because community energy networks, energy co-ops, microgrids and peer to peer energy transactions are beckoning. The availability of renewable energy will therefore no longer require the installation of onsite generation capacity but can be accomplished through other forms of investments and associated contracts. As these contracts are still emerging and consolidated cost models are not available, our investigation assumes that all electricity generation will come from onsite PV, with the usual site-specific constraints with respect to maximum installable PV area.

The measure to evaluate energy flexibility in buildings varies according to different definitions of energy flexibility (Six et al. 2011; Nuytten et al. 2013; De Coninck & Helsen 2013). There have been multiple methods to characterize the energy flexibility of buildings in the literature. Denholm et al. (2011) analyzed the energy flexibility in terms of the mixture of different forms of power plants (plants for the base, the intermediate, and the peak load) and concluded that reducing the share of the baseload power plants would increase the energy flexibility of the power supply system to incorporate increasing shares of variable generation. Huber et al. (2014)

suggested three metrics to characterize energy flexibility: ramp magnitude, ramp frequency, and response time. Lopes (2016) summarized that the two main EFMs in buildings are thermal energy storage and appliance operation shifting. Each method presented in the literature is distinguished from others due to different definitions of the energy flexibility. Therefore, a clear definition and a systematic way of quantifying energy flexibility need to be proposed. In this thesis, energy flexibility of a building represents the ability to flexibly adjust the daily load profile through effective communication and control technology without compromising the basic functions and the normal operation of the building.

Energy flexibility is an important concept in the context of this study, as there is an obvious inverse relationship between energy flexibility and demand charges. The control strategies and algorithms for obtaining energy flexibility include thermal storages, demand side management, on-site generation, and occupancy behavior in buildings, all of which could benefit building owners with reductions of their monthly demand charges. Likewise, demand charges, in some way, can also be interpreted as a penalization for buildings not being energy flexible enough. It puts an extra charge on buildings that cannot shift their load to off-peak hours. Investment in interventions for demand charge reduction can help improve the energy flexibility of the building and promote the future adaptive role in the smart grid. Energy flexibility can create quantifiable economic value, such as monthly bill savings and deferred infrastructure upgrades for both customers and the grid. This thesis discusses the potential of energy flexibility in three different types of commercial buildings and its economic value in terms of demand charge savings.

Energy flexibility allows demand to respond continuously to changing market conditions through price signals or other mechanisms. This expands the potential of the traditional demand response program, the concept of which will be elaborated in the next section.

2.4 Demand Response

The cost of electricity depends on various factors related to power generation and distribution processes and thus it is regarded as fluctuant by its nature, either for a short or a long term. For example, the cost of electricity significantly increases during peak hours when the stability of the grid is threatened. This is where the demand response (DR) programs come into play by motivating building owners to reduce their usage with incentive-based or price-based programs and ultimately to avoid the overloaded electricity demand during the peak hours of the day (Albadi et al. 2007).

DR is defined as a program that provides monetary incentives to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized (EIA 2016). DR includes all electricity consumption pattern modifications that lead building owners to alter the timing and the level of instantaneous demand, or total electricity consumption (IEA 2003). DR is regarded as an incentive-based program that encourages building owners to improve the energy flexibility of their buildings. Enrolling into a DR program requires the customer to reshape their usage profile, i.e. shaving the peak load and shifting the electricity use across hours of the day, which helps the building owner reduce the demand during peak hours thus save demand charges.

Georgia Power (GP)'s Demand Plus Energy Credit-3 is a DR program that will pay $6.25 per kW demand reduction plus $0.09 per kWh energy reduction to any customer who meets the required level of demand reduction in each billing month that includes a demand reduction period (DRP). The DRP is normally non-holiday weekdays, from 12:00 p.m. to 8:00 p.m in summer months when the outside temperature is higher than a certain value. The utility company will notify the customers one hour ahead of the DRP. If the customer's actual metered demand during the

DRP is greater than the limit they promised, the customer will be charged a compliance penalty of $3.50 for each kW for the amount above the limit during each hour of the DRP. This penal charge is regarded as an incentive for customers who react in the desired way to DR signals.

Different from DPEC-3, PG&E designs peak day pricing (PDP), which is a DR pricing plan released to complement time-of-use (TOU) pricing or replace flat rates in specific schedules. PDP provides lower energy prices during the summer in exchange for higher rates during certain hours on nine to fifteen peak event days per year. These event days can be triggered by forecasted high temperatures, high market prices, or California Independent System Operator emergencies. On these days, the cost of the electricity will increase during peak demand hours from 12 p.m. to 4 p.m. For instance, if the maximum forecasted temperature of tomorrow is above 30℃, the company will dispatch the PDP events. In the case of the PG&E rate schedule E19, the PDP charge is $1.2 per kWh and the credit is $5.92 per kW for the coincident peak power reduction (E19 2017). There is no direct penalty if the customer fails to reduce their power usage, but a higher energy rate during the event period applies.

DR is easily confused with the concept of demand charge since they both are related to the peak power in the power grid. Demand charge is a fee that is automatically charged by the utility company to the customer with high peak power demand in the service area. On the other hand, DR is a contract that the customer can opt-in, which allows the utility company active control over a part of the end use electricity with the aim to avoid the grid operating at near the full capacity. Both demand charges and DR are invented to improve the stability of the power grid by motivating building owners to adjust their electricity usage behavior through a penalty and reward system addressed at different types of customers. While demand charge is a mandatory charge that applies to large commercial and industrial consumers whose peak power exceeds a predefined level, DR is relevant to residential, commercial and industrial electricity users who are willing to sign up for a contract with the utility company to save on their electricity bills through incentives. Some utility companies will install remote control devices at the building owners to turn off some non-critical electric equipment while giving them corresponding incentives in advance. The end user and the utility company jointly decide which load can be adjusted and for how long.

In a typical DR program, building owners commit to reducing their usage during peak hours. If the heating or cooling system is curtailed as the way of reducing demand, i.e. leading to "consumption throttling", in most cases it will lead to the temperature setpoint not being met, thereby causing temporarily uncomfortable conditions inside the affected building. For example, when the demand in the grid is skyrocketing on a hot day, customers involved in DR are required (in many cases this is done by real-time automatic resets controlled by the utility company) to increase their thermostat setpoint, which may result in a temporarily uncomfortably warm exceeding the comfort level in their space. The desired result of DR is mostly that building owners shift the load to different times of the day, which can mitigate the negative effects on the thermal comfort as mentioned above, for instance, "pre-cooling" their spaces during the morning hours in advance (before the peak hours). DR programs provide customers the opportunity to manage their electric bills by reducing load during high demand periods or shifting load from high demand periods to low demand periods.

By motivating building operators to reduce or shift the peak load they exert on the grid, DR flattens the electric load profile, which reduces the risk of power shortages. When a heat wave in the state of New York in July 2013 led to a power shortage, effectively implementing DR successfully prevented the situation from getting worse. This event demonstrated the potential significance of the utility-controlled DR program (Sachen 2013). The typical methods used by participants to fulfill their DR obligations include: 1) turn off lights; 2) shut down equipment such as elevators and unused computer screens; 3) reduce Heating, Ventilation, and Air Conditioning (HVAC) system's electricity consumption through increasing temperature setpoints; 4) shift production processes with high power consumption to other time. It should be kept in mind that the design of the HVAC system is a relevant factor in this. On a hot day, the chiller will work at near maximum capacity. Manipulating the cooling setpoint may not have the desired effect, since the room temperature keeps rising above the new setpoint after the adjustment, which calls the chiller to come back on, most likely operating at its maximum capacity. To avoid this, some methods are introduced to manipulate the capacity of the chiller, e.g. through a voltage reduction. In that case, the chiller will act temporarily as a smaller system than its actual capacity thus reducing the peak load over the full period when the voltage reduction is activated.

2.5 Current Actions in the Power Market towards Reducing Peak Power

Local utility companies have created the DR program to help them manage the oscillating demand during extreme weather conditions in order to balance their operations. They also change the rate structure of electricity billing to increase the portion of demand charges. Arizona Public Service has submitted a proposed new rate structure designated to the residential sector to the Arizona Corporate Commission, which will impose a mandatory demand charge on the residential customer during the on-peak hours (Miessner 2016). Figure 2.4 explains the rate structure designed for the residential customer with the different amount of base load. This is not the only case that utility company requests mandatory demand charges for residential ratepayers. Exelon and ComEd in Illinois also tried to pass an energy bill SB 1585 with mandatory demand charges for residential customers (SB 1585 2017). Although all these efforts were denied by the judge, it reveals the attempts by the utilities to impede against increased peak power that can endanger the stability and safety of the power grid. On the other hand, utility companies need more funding to extend the capacity of the power grid to adapt to the fast growing peak load. Northeast Utilities will, for instance, invest 4.3 billion over the next five years to upgrade its transmission system in response to recent reliability concerns (NU Transmission).

Recently, a new trend emerges in the energy market that utility companies initiate the effort to help their customers retrofit their buildings in order to promote energy efficiency and reduce carbon footprint. For example, Xcel offers electric efficiency incentives and technical assistance to residential and commercial/industrial customers in the entire Minnesota service territory (Xcel's official website). Utility companies intend to make profits out of selling electricity to the market. Paradoxical to their main purpose, they start playing the role of an energy service company (ESCO) The profit is, of course, their major goal. As so many ESCOs in the market are making money out of conducting building commissioning and retrofitting, the utility companies seek opportunities to take a share of this market. Sitting on the primary seat in the power market as the energy provider, utility companies have a significant advantage over third parties. They have direct control over rate structures and the effect on their bottom line and know how performance contracts with their clients help their bottom line. Another factor that favors the utility company is that the government is now promoting energy efficiency in the power and building market. The State of Minnesota requires spending and savings targets for its utilities through an EERS. Xcel spent $91,385,776 on electric efficiency programs in 2015, while CenterPoint Energy spent $25,893,618 on natural gas efficiency programs and reported savings of sixteen MMtherms from natural gas efficiency programs in their demand side management report (Aceee database).

	Basic Service Charge (per mouth)	Demand Charge ($/kW)	Summer Energy Charge (On/Off Peak $/kWh)	Winter Energy Charge (On/Off Peak $/kWh)
Extra Small	$18	None	$0.10324	$0.10324
R-1	$24	$6.60/kW	$0.1516/$0.08070	$0.12730/$0.08070
R-2	$14.50	$8.40/kW	$0.1516/$0.0808	$0.12730/$0.0808
R-3	$24	$6.60/kW summer $11.50/kW winter	$0.0909/$0.05475	$0.06670/$0.05475

Figure 2.4 APS demand rate options

In the U.S., utility companies plan to invest an estimated one trillion in upgrading the conventional generation, transmission, and distribution infrastructures in the power grid to resolve stability and voltage quality problems caused by insufficient capacities over the next fifteen years (Dyson & Mandel 2015). However, the official forecast indicates that the trend of the power sales growth rate will be flat or even decline in the future, which would likely lead to increasing retail electricity prices.

Rising retail prices of electricity and declining costs of PV system imply that grid-connected PV systems will be economic within the next five years. The utility company could then face a significant decrease in power sales, which support the necessary power grid maintenance and upgrade. The solar system is thus recognized as both the biggest threat as well as opportunity in the utility business model. Sustainable energy sources, such as the wind and the solar power, have an intrinsic variability that can seriously affect the stability of the power grid if they account for a high percentage of the total generation. Future high penetration of variable distributed energy generation requires a dynamic load in order to match the instantaneous energy generation, which requires the efforts of every building operators to make their energy demand flexible to adapt to the dynamic change of power generation in the grid. Nevada ended net metering (a metering procedure that effectively makes the feedback price equal to consumer price) in their rates, which could cause 32,000 solar owners in the state to be underwater on their investments (Arizona Builder Exchange website). Likewise, utility companies tend to reduce the buyback rate of excess PV generation in order to make profits from selling electricity as well as reduce the threat from unpredictable and uncontrollable dispersed generation towards the stability of the power grid. In the long term, there is a danger that the conflicting business goals of utility and PV investors are not good for the healthy growth and development of the energy market.

Indeed, appropriately incorporating sustainable generation, such as from solar panels and wind turbines, in power systems on both the supply and the demand side can, to a large extent, help reduce the burden on meeting the capacity requirement in the power grid. At the same time, adopting renewable resources can lower the carbon footprint and prevent the destruction of the ecological balance. It is expected that with the increase of DER, the electricity system stakeholders need to reform their current rate structures, utility business model, and regulation of the power grid to accommodate DER. Reasonable and effective legislation regarding the solar industry needs to be proposed for the purpose of healthy growth and robust development of the power market.

This study starts from the assumption that peak power reduction by building owners is driven by their intentions of reducing their electricity bill. Various methods of reducing demand charges are subjects of previous studies. For example, Ma et al. (2014) employed an economic model predictive control method to optimize building demand and concluded that optimal pre-programming of temperature setpoint in the HVAC system can successfully shift major electricity load to off-peak hours thus reduces demand charges. Hanna et al. (2014) conducted a study to optimize the dispatch strategy of battery storage with the linear programming method. The author claimed that PV alone cannot perfectly reduce peak power but PV with a battery storage system does. Kim (2013) reported the demand-side control strategy with a thermal energy storage and the model-based predictive control method to deal with uncertainties that embedded in the simulation. The adaptive model-based predictive control of the thermal energy storage at night can provide an optimal solution to reduce the peak in the demand profile the next day. Salsbury et al. (2013) introduced a predictive control strategy to help a building reduce peak power. With vapor-compression cycle systems as an example, this study concluded that in small buildings, improving the energy efficiency of the system, which contributes substantially to the total energy cost, can significantly reduce the peak demand and energy consumption of the building throughout the day. Yin (2010) presented varied scenarios of DR strategies in terms of their effects on demand shifting and shedding during the peak period. The paper concluded that the peak demand savings increases as the building thermal mass increases, and that pre-cooling the building has a significant effect on flattening the electrical load profile without sacrificing the thermal comfort. The studies mentioned above have collectively defined the problem and investigated particular, mostly operational strategies to reduce peak power.

Important questions still remain unresolved regarding investment decisions of demand charge saving strategies. For example, what is the best optimization strategy to allocate an investment in light of so many correlated optimization factors? How will different building types require a different mix of technologies and operational strategies? In particular, what determines an effective trade-off between EEM and EFM investments? In other words, given a certain amount of initial investment, how could one maximize the investment benefit in terms of reducing demand charges on his monthly utility bill? If one wants to achieve a certain level of savings on demand charges, which technology does this at the lowest cost? What is the most significant factor that contributes to demand charges in a certain type of commercial building? This thesis will address those questions by analyzing the optimal investment strategy and exploring the multi-factor optimization space of demand charge reduction from the end user's point of view.

CHAPTER 3 APPROACH AND METHODOLOGY

3.1 Deterministic Analysis

The first step of this thesis is conducting a deterministic analysis of optimal investment strategies to reduce demand charges. In order to find the optimal investment strategy, this thesis proposes an optimal investment framework that is translated into an investment analysis instrument in the form of a spreadsheet based analysis tool. At its core, the tool contains a first-principle based energy model of the building. It is suited to analyze different types of commercial buildings under different EEM and EFM selection and governed by a particular rate structure.

In the deterministic study, a reduced-order building energy simulation model is created in the EPC (to be introduced below). The optimal investment strategy is tested with different rate structures and different building types. The parameter space of the optimization study comprises three categories of parameters: energy efficiency intervention, flexible building load control, and renewable energy. The parameterized realization is detailed in subsection 4.1.1. The ultimate optimization goal is to maximize the net present value (NPV) of the investment in EFMs over an investment time horizon of twenty years. The optimization process is carried out in Tech OPT (to be introduced below). Figure 3.1 illustrates the structure of the optimization platform for the deterministic analysis.

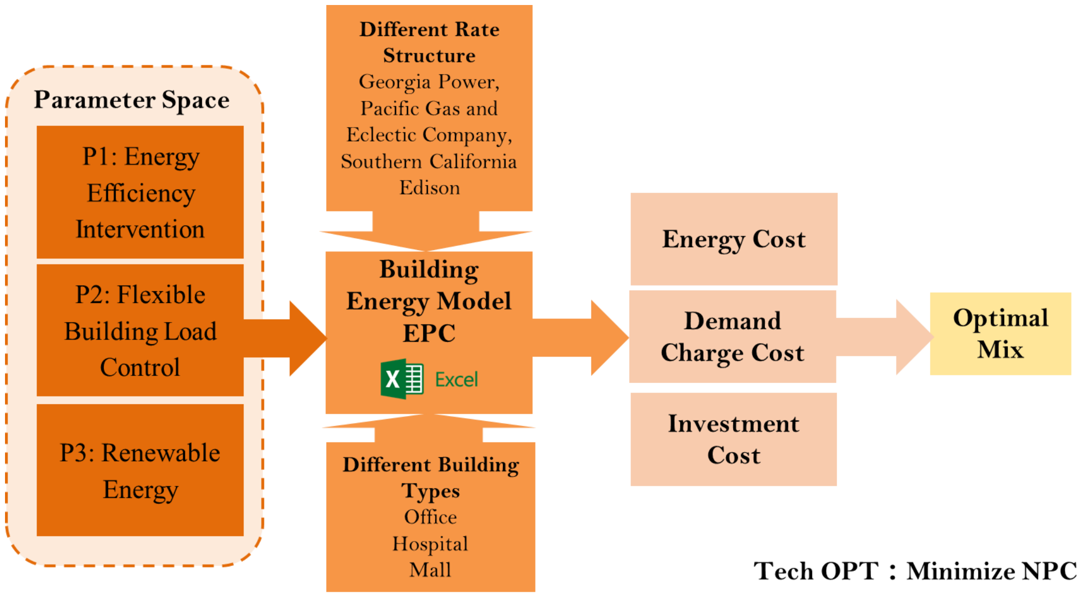


Figure 3.1 Optimization platform for the deterministic analysis

The starting point of this development is the EPC calculator (ISO 13790, 2008) and its add-on for optimization studies (EPC-Tech OPT). First, we will describe the EPC calculator. The inputs of EPC contain nine sections: building information, heat capacity, building system, building integrated energy generation system, energy source, zones, schedules, envelope, and material. Inputs of EPC match the information from drawings, building description, retrofitting reports and other supplementary materials as strictly as possible. However, due to the calculation method of ISO 13790, several inputs in EPC are “aggregate macro values” instead of the “specific technical parameters”. This means that certain components and their governing physical properties are provided by the modeler. For instance, only system COPs of the cooling system and heating system are considered in EPC, which is not the necessarily the COP of the heating/cooling device but takes all system related loss factors into account as well.

Tech OPT is an extension of the calculator that finds the best mix of a user-provided set of candidate technologies based on a user-defined target. Moreover, every technology has a predefined discrete set of achievement levels. Each achievement level is associated with an actual product in the market, with a specified cost of that product. In some cases, a technology achievement is continuous, as is the case with PV installation, assuming that the area of PV panels runs from zero to the maximum space available. Tech-Opt is an added feature to the EPC calculator that performs the optimization by finding the optimum technology mix (requiring the solution of a mixed integer continuous parameter optimization problem) given a certain criterion, such as minimum total cost within a time horizon. The optimization scheme uses the 'solver' add-in provided in Excel, and the input data provided in the EPC spreadsheet. There is no need for external software, file, or computational code.

There are various measures and technologies to help reduce demand charges as introduced in the previous chapter. Multiple energy model parameters are associated with the realization of these proposed measures and technologies at different achievement levels. The parameter set contains both physical parameters that characterize a technology and its achievement (EEM), as well as parameters that characterize an operational measure (EFM). This presents a complex optimization problem given the fact that so many factors are correlated to each other. In the multi-parameter optimization space, it is difficult to reach the optimum point without a solid exploration method through the space. Although this approach has been applied in other building optimization settings (Simmons et al. 2015), there is not a confirmed model that can generate the optimal solution to reduce demand charges for a given building and its baseline. This thesis proposes a generic method to find the dependency between optimization parameters that define the discrete technologies and operational schemes and their significance in terms of increasing energy flexibility and demand charge reduction.

3.2 Use of a Reduced Order Energy Simulation Software in Predicting Peak Demand

EPC is chosen for this study although it is well known that the reduced order model is inherently limited in simulating the fast dynamics of temperature changes. Moreover, the inherent hourly time step that EPC uses will by necessity underestimate the real peak that may occur for fifteen minutes within the hour. This drawback does not only exist in EPC but is actually a typical weakness of the conventional energy simulation software given the fact that building peak load estimation is instantaneous and hard to be averaged out over a longer interval measurement period. This fact is typical of no consequence in the estimation of building total energy consumption. In other words, the estimation of the total energy usage in a month is accumulative of hourly energy consumption over all hours in the month, while the peak demand is only accumulative energy over a very short time period, typically fifteen minutes. The reduced order model only supports one-hour resolution of simulation while the utility looks at demand in a 15-minutes or maximum 30-minutes time window. The longer the time window, the less the peak demand, which means that using the 1-hour time window reduces the value of peak power mathematically since it averages out the peak power that occurred sometime during the one hour period. Although less of an issue in aggregated energy consumption studies, the peak demand plays a potentially significant role in our peak load analyses.

Another drawback of EPC is that when calculating the load of the building, it treats the whole building as one combined zone, realized as one lumped node with an internal capacity factor representing the capacity of the “active” interior building elements. In reality, in office buildings, the perimeter zone reacts differently for differently orientated facades of the building. Whereas one perimeter zone (e.g. north) may require heating, another zone may need cooling. This effect is ignored as all loads are added together (positive and negative canceling each other out) ignoring the consumption resulting from simultaneous heating and cooling.

However, one must recognize that the optimization studies in this thesis are all based on comparative analysis, i.e. calculating the relative improvement of the consumption and peak load reduction as the result of a set of particular improvement measures over a baseline. Adequacy for comparative analysis requires a much lower standard for the fidelity of the simulation tool (Kim et al. 2013). Nevertheless, it is necessary to validate the reduced order model to verify that its substantial benefits in computational simplicity outweigh the potential inaccuracies. A validation experiment will be carried out in Chapter 7 with EnergyPlus as the higher fidelity model. The result of the validation study should confirm that a reduced order model like EPC is sufficiently accurate for the purpose of optimization as targeted in this thesis. The purpose is to provide sufficient confidence that our approach is adequate for the determination of the optimum mix of EEMs and EFMs for demand reduction.

3.3 Optimization Parameters and Technologies

The optimization parameters considered in this thesis can be categorized into three types: energy efficiency intervention, flexible building load control, and renewable energy. Table 3.1 gives an overview of the parameters that will be explained below. In energy efficiency interventions, five parameters are considered as input variables that will impact the peak power, coincident peak power and total energy consumption of the building. Infiltration or air leakage refers to the unintentional or accidental introduction of outside air into a building. Insulating the exterior opaque envelope of the building reduces transmission losses and gains. This is a typical EEM in the building retrofit project. The emissivity of the roof refers to the ability of the surface material on the roof to re-radiate the absorbed solar radiation back to the sky, which relates to the amount of total heat that is emitted by the roof material after the heat is absorbed. The solar reduction factor of the window represents the permanent installation of external shading devices or internal window treatment, which reduces the global transmission of solar radiation. (ISO 13790 Annex G.5.2). The Solar Heat Gain Coefficient (SHGC) of the window is defined as the fraction of incident solar radiation that enters into the interior space through the window in the form of direct radiation and heat from absorbed solar radiation in the window and internal shades (an indirect result of radiation). The procedure for testing window products and assigning SHGC ratings is performed by the National Fenestration Rating Council (NFRC) first started in 1993. Solar heat gain through windows is a significant factor that will impact the cooling load in commercial buildings.

In the operational building load control, three parameters are considered as input variables that will impact the peak power, coincident peak power and total energy consumption of the building. Temperature control of the building refers to setting the thermostats that can be set toward the bottom of the comfort zone instead of the top (at 25℃ instead of 22℃, for example) from 12 p.m. to 4 p.m. in summer months to reduce coincident peak. The lower temperature allows the air–conditioning compressor to be turned off or its output to be reduced for short periods without raising the temperature enough to bother occupants. Lighting dimmers installed in the lighting system can be used to control the lights in certain areas of the building from 12 p.m. to 4 p.m. in summer months to reduce the coincident peak. Voltage throttling with voltage-reduction controllers could effectively lower the coincident peak demand and energy over time by regulating the voltage output of high power-consuming equipment, i.e. chillers. Load shifting by changing the usage policy and time of high power-consuming equipment can shift building loads to times when electricity prices are lower and to reduce peak demands. In renewable energy, installing a certain size PV system is considered as an input variable that will impact the peak power, coincident peak power and total energy consumption of the building. The factor related to on-site renewable generation is the area of the PV system. The PV system installed on the roof can generate electricity during a clear day with sufficient solar radiation.

Table 3.1 Category of demand charge reduction intervention

	Building Parameters
Energy Efficiency Intervention	Infiltration Rate
	Wall Insulation Thickness
	Emissivity of Roof
	Solar Reduction Factor
	Window SHGC
Flexible Building Load Control	Temperature Control
	Lighting Dimmer
	Voltage Throttling
	Load Shifting
Renewable Energy	Area of the PV System

Among the three categories of optimization parameters, the energy efficiency interventions impact the "steady" building load in terms of permanently changing the physical property of the building to improve its thermal performance. The dynamic control and renewable generation strategies help to improve the energy flexibility of the building. The load/energy flexibility of a building refers to the ability to control its power demand and generation to adapt to the local climate conditions, user needs and grid requirements (Huber et al.2014 and Blarke 2012). The impact of both the static interventions as well as the dynamic interventions on the reduction of peak demand will be analyzed in Chapter 4. The correlation between optimization factors will also be discussed in the studies presented in Chapter 4.

For building owners who want to reduce or eliminate electricity demand charges, the first step is to understand which factor contributes significantly to the peak demand as calculated in the demand charge formula that the local utility has implemented. A recent study shows for example that one major peak power contributor could be the hydraulic elevator inside the building. The fluid in the hydraulic fluid tank needs to be heated through the friction of circulation inside the water pump in order to remain at the normal operational temperature range. If the elevator is seldom used, heating up the fluid consumes a lot of energy and will cause spikes in the demand profile. To avoid the friction heat process, which can be a big peak demand contributor, one approach is to install an accessory heater as a heating source (Calderwood 2016). It should be noted that these incidental contributors to the peak load are not considered in our study as their impact is hard to generalize. In most cases, their impact is relatively small. In office buildings, the HVAC system and lighting system are generally considered to be the top two energy consumers. This raises the question whether they are also the top causes of demand charges. The deterministic analysis in Chapter 4 will present the outcomes and discuss the top-ranked contributors to demand charges under different rate structures.

3.4 Influential Parameters on Peak Power in the Building

There are many fixed design factors that do not belong to the optimization parameter pool proposed in section 3.3 but have a major influence on the peak power of the building. It is important to single out two major factors: the size of the building and cooling capacity of the HVAC system. They are discussed in the following subsections.

3.4.1 Size of the Building

Demand charges apply to commercial and industrial buildings, which consume more energy compared to the residential sector and are more prone to have a high peak power demand. The utility company charges their customers whose monthly or seasonal total energy consumption or billing demand exceeds a certain predefined threshold. When we evaluate the energy performance of a building, the Department of Energy (DOE) establishes a normalized baseline of energy consumption known as performance indicators and help building owners locate their usage level of energy among peer buildings. When the utility company evaluates how much they should charge their customer on peak demand, they base their charges on the overall building peak demand (kW) instead of normalized peak demand, e.g. peak intensity (kW/m^2). This raises the question whether it would create a fairer assessment if peak demand is evaluated on an intensity basis (kW/m^2). To answer the question, a comparative study is carried out with variable building area. We conduct the analysis for an office building. The properties of the building envelopes are fixed, and the internal loads are defined with fixed density and schedules. Table 3.2 lists the design variables including building area, building height, building volume, cooling capacity for the comparative study and the outcomes of the study including the peak demand and intensity of peak demand. Figure 3.2 shows the trend of the peak demand as the building size increases. The result implies that as the size of the building increases, the peak demand is linearly increasing while the intensity of peak demand remains flat. In most of the current utility rate structures for demand charges, charges will kick in when building demand exceeds 200 kW. When the peak exceeds this threshold, the building will incur a higher rate compared to those below 200kW even though the normalized peak power per square meter remains the same. As the charge thus keeps increasing with building size, the owner could save theoretically by building two separate smaller buildings that keep their individual peak demand under 200 kW. It is understandable that utility companies want to create a revenue stream through the design of rate structure as a market instrument to flatten the power demand curve, that ultimately reduces the cost of the distribution network. GP's PL tariffs (PL-Small, PL-Medium, and PL-Large) have an hours use of demand (HUD) structure, which charges their customer based on their total energy consumption as well as the usage frequency (GP PLL).

$$\text{HUD} = \text{Monthly consumption (kWh)}/\text{Billing demand (kW)}$$

It is a typical rate structure that utility companies adopt to charge their customer based on the total energy usage and the more they use, the less unit rate they pay for energy, the higher rate they pay for demand charges. However, to stimulate the healthy growth of the market, they should also consider the fairness of the rate structure. When considering demand charges, should there be a credit for a building, which is larger in size but has a lower peak power intensity compared to peer buildings? In the current rate structure, demand charge is calculated based on the total peak demand. In light of a trend that future buildings are on average have a larger size (EIA 2016), should the utility take the intensity of demand in consideration to make the pricing mechanism in the electricity market fairer? This warrants a comparative analysis of the per unit floor area cost-saving on demand charge reduction in a large building versus a small building. With the same amount of demand charge reduction, if the cost per unit floor area in a large building is higher than in a small building, it will add additional unfairness to the current rate structure.

Table 3.2 Intensity of the peak power with changing building size

Building Area (m^2)	500	1000	1500	2000	2500	3000	3500	4000
Building Height (m)	4	8	12	16	20	24	28	32
Building Volume (m^3)	2000	4000	6000	8000	10000	12000	14000	16000
Cooling Capacity (W)	50000	100000	150000	200000	250000	300000	350000	400000
Peak Demand (kW)	44.41	88.81	133.21	177.55	221.97	266.33	310.71	355.3
Intensity of Peak Power (W/m^2)	88.81	88.81	88.8	88.78	88.78	88.78	88.77	88.77

Table 3.2 details the physical properties of the building in comparative studies and the change of peak demand (kW) and its intensity (W/m^2) as the floor area increases. Figure 3.2 depicts the trend of peak demand and intensity of peak demand when the floor area is increased. The

results of the comparative analysis imply that as the total floor area increases, the peak demand linearly increases with size while the intensity of the peak demand remains at a steady value with a slightly decrease on the resolution of 0.01W/m^2, which could be ignored. If the future study reveals that a building with larger size indeed spends more money with the same amount of demand charge savings compared to the smaller one, the fairness of current rate structure design would be doubtful since the intensity of peak demand in a large building is the same as in a small building while the demand charges are substantially higher. In the current study, such a comparative investment analysis along the size axes is not conducted, as this is left to a follow-up investigation that could be straightforwardly conducted with the tool developed as part of this thesis. We will, however, compare three different building types. As size is an important factor, the comparison of different building types needs to be conducted for buildings that are comparable from the perspective of demand charge. It will be explained in the next chapter how the size of the three baseline buildings (for office, hospital, and retail) have been chosen to provide an equal playing field for the three buildings to compare different measures for demand charge reduction.

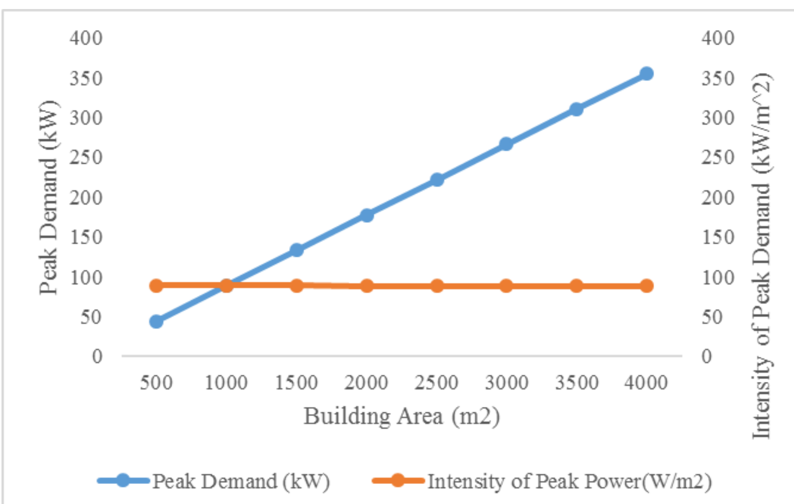


Figure 3.2 Trend of peak demand and intensity with increased building floor area

3.4.2 Cooling Capacity of the HVAC System

The HVAC system is considered to be the biggest energy consumer and in many cases causing the highest power demand in commercial buildings (EIA 2011). Properly sized HVAC systems should be able to fulfill the cooling and heating requirement and to maintain the desired level of thermal comfort for the occupant inside the building (Thomas and Moller 2007). Existing methods to size the HVAC system include standard design methods issued by ASHRAE in the U.S. and CIBSE in United Kingdoms. The load calculation and system sizing method introduced in the ASHRAE Handbooks of Fundamental (ASHRAE 2009) is the most widely accepted method in the U.S. Mechanical engineers design the HVAC systems based on the design day method that defines the building's heating and cooling need. A safety factor is introduced to the calculated load in order to manage the risk of an undersized system, which would fail to produce adequate cooling or heating during operational hours. However, the choice of the safety factor is highly dependent on the personal experience of system design experts, who seek to minimize the probability of system failure and the associated professional risk. A "conservative" design can easily lead to an oversized system. Felts and Bailey (2000), Djunaedy et al. (2011), and Woradechiumroen et al. (2014) claimed that the system oversizing culture is quite common in the current HVAC system design industry with some systems being oversized by 100%.

Existing studies have shown that an oversized system could lead to increased initial and operational costs, and inefficient usage of the system with components running at low efficiency curves most of the time (Djunaedy et al. 2011; Jacobs 2003; McLain et al. 1985). Ruya and Augenbroe (2016) claimed that generic HVAC system sizing methods can cause oversizing in many cases and propose a risk conscious way of "right sizing" HVAC systems. The result of this study proved that even if the system is 10% downsized, the number of unmet hours is still within an acceptable range. Above studies have revealed that oversized system only increases the ability to deal with a large instant cooling load, which only occurs at best a few times in a year and lead to an unnecessary waste of operational cost with increased energy usage. For demand charges, another effect of oversizing enters the equation, i.e. as larger system guarantees that at certain peak days the peak load may increase with the maximum capacity of the chiller if indeed such peak loads should occur. It is, therefore, necessary to study how downsizing or temporary voltage reduction at peak hours (both have essentially the same effect) will affect energy flexibility and therefore demand charges. A comparative study is conducted to analyze the impact of system capacity on the peak demand of the building.

Table 3.3 demonstrates the result of this comparative analysis. In the comparative study, the baseline building's cooling system capacity is sized according to Chapter 14 of the ASHRAE Handbook of Fundamental (ASHRAE 2009), which introduces cooling, dehumidification, and enthalpy design conditions. Among these design day conditions, the 0.4% occurrence dry-bulb and mean coincident wet bulb temperatures represent conditions on the hottest, sunny days with highest dry bulb temperature. The sizing of the cooling system in the baseline building with safety factor equals to one is based on this design day condition. The comparative study below varies the safety factor from 0.9 to 1.1 to study the impact of system sizing. Installation cost of the cooling system is based on market data analysis, leading to an average cost of a cooling system of $700 per cooling ton. The demand charge rate structure is based on PG&E's schedule A-10. The demand charge rate is $16.78 /kW for a building's billing demand exceeding 200 kW while staying below 499 kW. The cost of loss of productivity is calculated by multiplying the worker's hourly salary with the percentage loss of productivity, which is based on the conclusion of thermal comfort research that when the temperature in the space is higher than a certain value, the productivity of the workers in the space will decrease (Seppanen et al. 2004).

Table 3.3 Comparison of the economic effects of different sizing factor

Safety Factor	System Capacity (W)	Unmet Hours	Peak Demand (kW)	Installation Cost ($)	Demand Charges ($)	Loss of Productivity ($)
0.90	256500.00	44	242.00	51054.21	4060.76	310.00
0.95	270750.00	11	250.00	53890.56	4195.00	24.00
1.00	285000.00	0	258.00	56726.90	4329.24	0.00
1.05	299250.00	0	266.00	59563.25	4463.48	0.00
1.10	313500.00	0	270.00	62399.59	4530.60	0.00

It is worth mentioning that the system cooling capacity could impact the peak demand in two ways. On the one hand, an oversized system will run at the low side of the efficiency curve and which leads to a waste of energy compared to a smaller size system. On the other hand, if there is an instantaneous big cooling demand inside the building (e.g. a few times a year), an oversized system will run at full capacity, which creates an instant spike in the electricity usage profile of the building, while a smaller system will, in that case, lead to a lower peak but with obviously a (short) period of unmet load resulting in unmet hours. Table 3.3 indicates that when the system designer adopts the 0.9 safety factor, the unmet hours will increase to 44. The unmet hours will impact the productivity of the occupancy. It can be seen that increasing the safety factor does not significantly reduce the unmet hours but increases the installation cost and demand charges substantially. It can be concluded that in this case using standard sizing (safety factor = 1) or under-sizing the system (safety factor = 0.9) is cost effective. Increasing the safety factor not only increase the installation cost but also could increase the monthly demand charges. It should be kept in mind that the above study is in no way generic. It is done at this early stage to understand the major implications of system size choice in the baseline building used in the studies conducted in this thesis. It can be concluded that system size is not a major influence on demand charges. We will, therefore, determine the size of the chiller in the three baseline buildings with the standard ASHRAE method with safety factor one.

3.5 Stochastic Analysis Framework

After conducting the deterministic analysis, an extended framework for determining optimal measures for demand charge reduction will be introduced with the recognition of the effects of all possible sources of uncertainty. Figure 3.3 describes the structure of the analysis framework. The uncertainties in physical parameters, usage scenarios, cost models, productivity loss models, future demand charge rates, and deterioration of the performance of certain technologies can then be considered when making the investment decision. The quantification of those uncertainties will be based on the uncertainty quantification (UQ) repository developed in previous work in the EFRI-SEED project (Sun 2014). The context of this thesis requires additional parameter uncertainty quantifications hitherto not attempted. This pertains to “external costs” such as the uncertainty in the technologies of certain measures and in the future change of the demand charge rates. In addition, this thesis will quantify the uncertainty in the function that describes the productivity loss in response to the temporary change of the thermostat settings and hence operative temperature (Seppanen et al. 2004). The results of these new characterizations will be added into the generic UQ repository for future general use.

Rationally finding the optimum investment decision in recognition of uncertainties requires the introduction of a stochastic optimization approach driven by preference criteria of the building owner and operator. Rather than employing axiomatic utility theory, this research step is based on a heuristic “robustness” criterion. Defining such a criterion and using it in the optimization is a major intellectual challenge that does not fit in the scope of this thesis. In lieu, we will introduce a number of plausible risk preference profiles and show the outcomes for these heuristically determined profiles. Stochastic optimization will be carried out with @Risk software (Palisade Corporation 2017), which is a risk analysis software using Monte Carlo simulation for Excel.

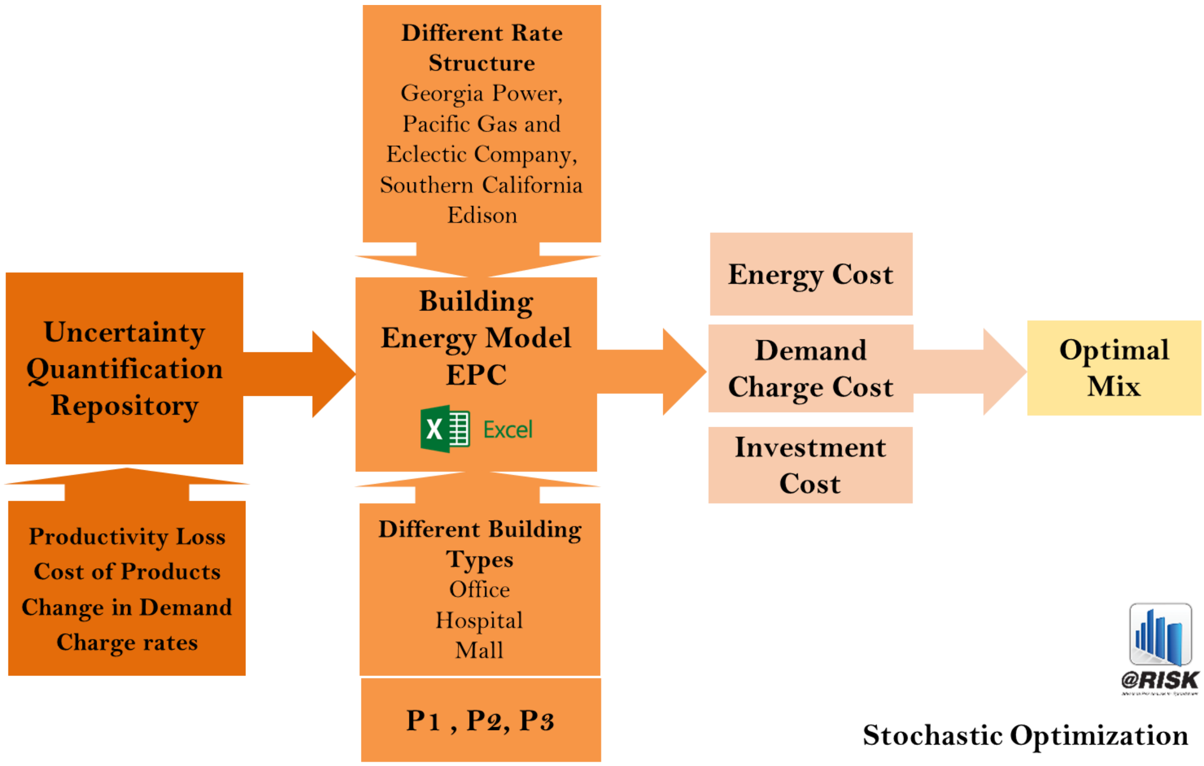
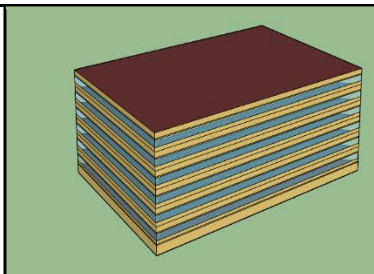
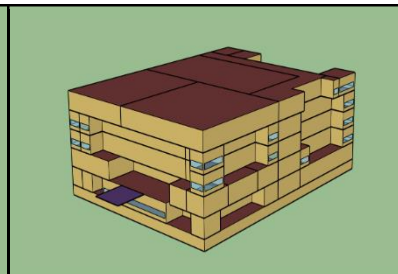
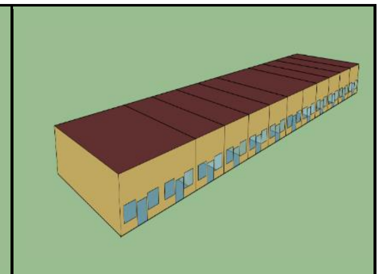
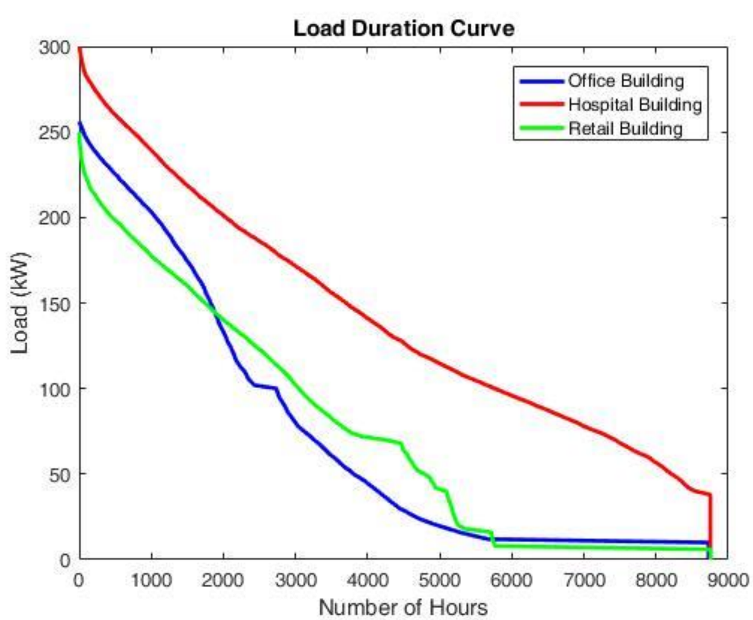


Figure 3.3 Optimization platform for the stochastic analysis

CHAPTER 4 DETERMINISTIC ANALYSIS

This chapter carries out the deterministic analysis of the optimal investment strategy for three prototypes of commercial buildings: an office building, a hospital building, and a retail building. The baseline models are taken from the U.S. Department of Energy (DOE) prototype commercial building models (DOE website), which satisfy the requirements of ASHRAE Standard 90.1-2010. Table 4.1 shows basic information of the prototype building model.

Table 4.1 Prototype model information

Building Model			
Building Type	Office	Hospital	Retail
Floor Area	3000 m^2	3000 m^2	3000 m^2
Load Duration Curve			

It is worth mentioning that the original floor area of the prototype building in the DOE library is different from the values listed in Table 4.1 as used in our study. As addressed in section 3.4.1, the total floor space in the building impacts the peak demand. To eliminate the impact of floor space and gain a deeper and more straightforward understanding of demand reduction over different types of commercial buildings, all three prototype building models are scaled up or down to 3000 m^2. Figure 4.1 illustrates the hypothetical change of peak demand in these three prototype buildings as the floor area increases. To conduct a fair comparison of the optimal investment strategy among different types of buildings, we need to match them either horizontally (same peak demand) or vertically (same floor area). In this study, we scale them to matching floor areas.

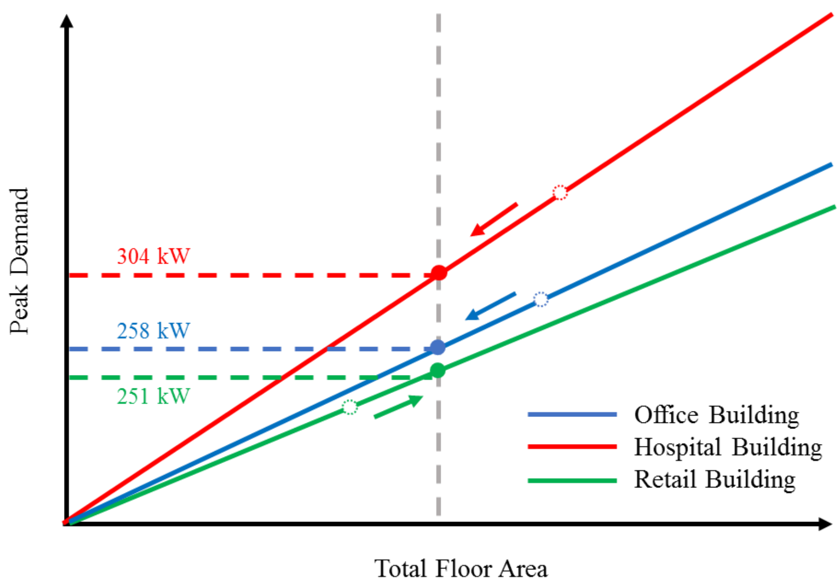


Figure 4.1 Strategy for baseline building choice for analysis

Based on the strategy depicted in Figure 4.1 we construct the baseline buildings for the 3 types. It can be seen that the peak power before any measures ranges from 251 to 304 kW. This range is narrow enough to put all three buildings in the same range of demand charges, thus making the comparison of measures realistic and relevant. For a full coverage of size and type variations, the coverage of size and peak load should cover a large area of Figure 4.1. This is left to future follow-up work. The optimal investment solution with a mix of interventions will be tested for each type of commercial building under five different rate structures. Therefore, each analysis of the optimal solution for a certain type of reference building consists of five cases, representing the different rate structures. For details of rate structures, refer to Appendix.

Case 1 adopts the rate structure of GP's schedule PLM-11 in the electricity bill calculation and optimization analysis. Schedule PLM-11 (PLM-11) is designed for any customer with a demand higher than 30 kW but less than 500 kW. GP charges its customers $8.24 per kW of billing demand. The energy rate is based on HUD, which is based on the customer's total energy consumption as well as the usage frequency. Table 4.2 lists the energy rate of PLM-11. There is no TOU rate or DR incentive in PLM-11. Appendix A details the rate structure of PLM-11.

Table 4.2 Electricity rate of GP PLM-11

HUD		Energy Rate($/kWh)
HUD < 200	First 3,000 kWh	0.112561
	Next 7,000 kWh	0.103091
	Next 190,000 kWh	0.088885
	Over 200,000 kWh	0.068955
200 < HUD < 400		0.011437
400 < HUD < 600		0.008606
HUD > 600		0.007486

Case 2 employs the rate structure of PG&E's schedule A-10 for medium general demand-metered service option A. Schedule A-10 (PG&E A-10) is designated for any customer with a demand higher than 200 kW but less than 499 kW. Option A in schedule A-10 is non-TOU rate structure with a daily flat energy charge. Demand charge rate in option A of schedule A-10 is $16.78 per kW in summer months and $9.45 per kW in winter months. The total energy rate is

$0.16492 per kWh in summer and $0.12832 per kWh in winter. There is no TOU rate or DR incentive in A-10. The cost per kWh only varies by season but not by the time of day. Appendix B details the rate structure of A-10 option A.

Table 4.3 TOU rate of PG&E A-10 and PG&E A-1

		Energy Rate ($/kWh)	
		PG&E A-10	PG&E A-1
Summer	Peak	0.21972	0.25943
	Partial-Peak	0.16459	0.23578
	Off-Peak	0.13652	0.20842
Winter	Partial-Peak	0.13641	0.21692
	Off-Peak	0.11935	0.19601

Case 3 applies the rate structure of PG&E's electricity schedule A-10 for medium general demand-metered service option B. Option B in schedule A-10 is a TOU rate structure with the energy cost varying by season and time of day. In the TOU rate schedule, rates are higher when the demand for energy is highest, which generally occurs during midday and early evening. Demand charge rate in option B of schedule A-10 is $16.78 per kW in summer months and $9.45 in winter months. If the optimization package could bring the billing demand below 200 kW, the rate calculation method will switch to schedule A-1, in which no demand charge applies. Table 4.3 lists the energy rate of A-10 and A-1. The definition of on-peak, partial-peak and off-peak hours is detailed in Table 2.1. Appendix C details the rate schedule A-10 option B. Appendix D illustrates the rate structure of schedule A-1. Option B of schedule A-10 has PDP credits, which is a DR incentive. Customers enrolled in A-10 will be charged $0.9 per kWh during the four-hour event period. In contrast, they will receive a credit of $3.26 per kW on the maximum summer peak power reduction and a reduced energy rate during non-event period.

Case 4 adopts the rate structure of SCE's schedule TOU-GS-3 option A. Schedule TOU-GS-3 option A is designated for any customer with a demand higher than 200 kW but less than 500 kW. If the optimization result could bring the billing demand below 200 kW, the rate calculation method will switch to schedule TOU-GS-2 option A. Option A in schedule TOU-GS-3 and TOU-GS-2 is a TOU rate structure with the energy cost varying by season and time of day. Table 4.4 lists the energy rate of schedule TOU-GS-3 and TOU-GS-2. The definition of on-peak, partial-peak and off-peak hours is detailed in Table 2.1. In option A of TOU-GS-3 and TOU-GS-2, customers will be charged \$17.81 and \$15.48 per kW of billing demand correspondingly. Appendix F and H detail the rate structure of schedule TOU-GS-3 and TOU-GS-2 option A.

Table 4.4 TOU rate of SCE GS-3 and GS-2

		Energy Rate ($/kWh)			
		SCE TOU-GS-3 Option A	SCE TOU-GS-3 Option B	SCE TOU-GS-2 Option A	SCE TOU-GS-2 Option B
Summer	Peak	0.31634	0.11537	0.34167	0.11665
	Partial-Peak	0.10999	0.07813	0.11601	0.07921
	Off-Peak	0.05944	0.05944	0.05918	0.05919
Winter	Partial-Peak	0.0738	0.0738	0.07589	0.0759
	Off-Peak	0.0643	0.0643	0.06573	0.06574

Case 5 employs the rate structure of SCE's schedule TOU-GS-3 option B. Schedule TOU-GS-3 option B is designated for any customer with a demand higher than 200 kW but less than 500 kW. If the optimization result could bring the billing demand below 200 kW, the rate calculation method will switch to schedule TOU-GS-2 option B. Option B in schedule TOU-GS-3 and TOU-GS-2 is a TOU rate structure with the energy cost varying by season and time of day. Different from previous rate structures introduced in this chapter, option B in schedule TOU-GS-3 and TOU-GS-2 includes a continuously active facility-related demand charge and additional time-sensitive demand charges. Option B of TOU-GS-3 charges \$17.81 per kW of facility-related billing demand throughout the year. In summer months, time-related demand charges will be added, which equal to the sum of $17.42 per kW of on-peak demand and $3.43 per kW of partial-peak demand. Option B of TOU-GS-2 has the same rate structure but a relatively lower rate. Appendix G and H detail the rate structure of schedule TOU-GS-3 and TOU-GS-2 option B.

Customers in option B of TOU-GS-3 and TOU-GS-2 could decide whether they want to opt-in a DR contract, which is the critical peak pricing (CPP) rate structure. If building owners choose to enroll in a CPP plan, the energy rate will increase to $1.3745 per kWh during CPP event. On the contrary, they could get a credit of $11.44 per kW reduction of the on-peak demand. The maximum number of the CPP event is limited to 12 each year, each lasting 6 hours. Appendix E and I detail the rate structure of CPP in schedule TOU-GS-3 and TOU-GS-2.

Table 4.5 List of five cases in the analysis of each type of commercial buildings

<table>
<tr><th rowspan="2"></th><th rowspan="2">Rate Structure</th><th rowspan="2">DC Threshold (kW)</th><th colspan="2">Demand Charge Rate ($/kW)</th><th colspan="2">Energy Rate ($/kWh)</th><th rowspan="2">Coincident Peak</th><th rowspan="2">TOU</th><th rowspan="2">DR</th></tr>
<tr><th>Summer</th><th>Winter</th><th>Summer</th><th>Winter</th></tr>
<tr><td>Case 1</td><td>GP PLM-11</td><td>35-500</td><td colspan="2">8.24</td><td colspan="2">Table 4.1</td><td>No</td><td>No</td><td>No</td></tr>
<tr><td rowspan="2">Case 2</td><td>PGE A-10 Non TOU</td><td>200-499</td><td>16.78</td><td>9.45</td><td>0.16492</td><td>0.12832</td><td rowspan="2">No</td><td rowspan="2">No</td><td rowspan="2">No</td></tr>
<tr><td>PGE A-1 Non TOU</td><td>75-200</td><td colspan="2">0</td><td>0.16492</td><td>0.12832</td></tr>
<tr><td rowspan="2">Case 3</td><td>PGE A-10 TOU</td><td>200-499</td><td>16.78</td><td>9.45</td><td colspan="2" rowspan="2">Table 4.3</td><td rowspan="2">No</td><td rowspan="2">Yes</td><td rowspan="2">Yes</td></tr>
<tr><td>PGE A-1 TOU</td><td>75-200</td><td colspan="2">0</td></tr>
<tr><td rowspan="2">Case 4</td><td>SCE TOU-GS-3 Option A</td><td>200-500</td><td>17.81</td><td>17.81</td><td colspan="2" rowspan="4">Table 4.4</td><td rowspan="2">No</td><td rowspan="2">Yes</td><td rowspan="2">No</td></tr>
<tr><td>SCE TOU-GS-2 Option A</td><td>20-200</td><td>15.48</td><td>15.48</td></tr>
<tr><td rowspan="2">Case 5</td><td>SCE TOU-GS-3 Option B</td><td>200-500</td><td>17.81+17.42+3.43</td><td>17.81</td><td rowspan="2">Yes</td><td rowspan="2">Yes</td><td rowspan="2">Yes</td></tr>
<tr><td>SCE TOU-GS-2 Option B</td><td>20 -200</td><td>15.48+17.32+3.38</td><td>15.48</td></tr>
</table>

Table 4.5 lists the five cases with different rate structures that will be taken as input in our study. In case 1, both the energy and demand charge costs are flat rates proportional to the actual usage. In case 2, the billing demand can be reduced below the charge's threshold (200kW), which could lead to a big difference on the annual utility bill. In case 3, the daily electricity price is no longer a flat rate but varies according to season and time of day, and a DR rate structure is included. In case 4, the electricity price is a TOU rate structure. In case 5, demand charges include time-

correlated coincident peak demand, which is measured during certain hours in summer months. Comparing the optimal strategy for cases 1, 2 and 3 could reveal the impact of a demand charge threshold and the TOU rate structure on the optimal choice of measures and the associated investment. Comparing the optimization results for cases 3 and 5 could illustrate the different impact of the coincident peak demands to the selection of the optimal set of measures. Rate structures in the five cases described above reflect different utility strategies, and by comparing their impact on the optimal set of measures, we will gain a deeper understanding of how utility rate structures change the market response and lead to different retrofit investment choices.

In each case, the following analysis will be carried out：

- Analyze the variability and sensitivity of peak load and energy consumption for the range of EEM and EFM
- Calculate the monthly electricity bill
- Determine the cost-optimal selection of EEM/EFM
- Financial analysis of the investment on EEM and EFM

The monthly bill will be calculated based on the rate structure designed by different utility companies. A detailed calculation of the utility bill in August will be illustrated as an example in each case.

The next step is searching for the optimal investment strategy that maximizes the NPV of the investment over a 20-year period. The impact of EEMs and EFMs will be separated in the optimization analysis, thus two consecutive optimization analyses will be presented. The first one finds the optimal combination of EEMs that maximizes the NPV for a specific budget ceiling as explained below. We will consider 5 distinct budgets between 0 and a maximum as determined by the application of all EEM at their maximum achievement level. Budget level 1 represents the baseline building with no EEM, i.e. with zero budget. In each of the following budget levels, there is a $50,000 increment in the capital budget compared to the previous one. At budget level 5, the budget reaches $200,000, which is determined for the given building as the budget that is necessary to apply all technologies and at maximum achievement level. The second optimization searches for the optimal combination of EFMs that maximizes the NPV for each of the five budget levels. The values of EEM parameters in this second optimization are the outcomes of the first optimization study and fixed at those values. The intent of this separation is to observe the impact of energy efficiency features on the selection of EFMs. It is expected that in general, the role of EFM diminishes as more is invested already in EEM. In the optimization study, the relative economic significance of EEMs and EFMs will be analyzed. One objective of the analysis is to reveal the mechanism of how specific demand charge rates lead to different investment choices. The other objective is to show whether after implementing EEM with increasing available budgets, the role of EFM will diminish.

We also conduct a sensitivity analysis to find out the most influential factors and to offer insight into the optimal investment strategy for five different rate structures. All analyses in this chapter are conducted with the reduced order simulation, i.e. the hourly EPC (ISO 13790, 2008) introduced in Chapter 3.

4.1 Reference Office Building

The reference office building is located in Atlanta, GA. The total area of the six-story building is 3000 m^2. The setpoint temperature of the building is 21℃ for heating and 24℃ for cooling. The primary energy source for heating and domestic hot water is natural gas, and the primary energy source for cooling is electricity. The maximum cooling capacity of the chiller is 285 kW. Table 4.6 lists the simulated monthly peak demand and consumption. The summer peak load is 257.96 kW occurring in August. Figure 4.2 illustrates the categorical distribution of annual energy in the office building. Cooling and lighting are the top two energy contributors respectively.

4.1.1 Sensitivity Analysis

SA is defined as “the study of how uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model input” (Saltelli et al. 2004). SA aims to answer the questions “which of the input variables influences the model output variance at most?” (Schwieger, 2004). Mechri et al. (2010) implemented variance-based methods to identify the design variables that have the most impact on the variation of the building energy performance for a typical office building. Ruiz et al. (2012) also identified the most influential parameters affecting the final energy consumption in office buildings with variance-based methods.

Table 4.6 Monthly peak demand and energy consumption

	Peak Demand (kW)	Monthly Total Power (kWh)
Jan	175.67	32305.48
Feb	217.50	34612.50
Mar	231.59	51876.44
Apr	238.28	54453.42
May	256.66	67682.24
Jun	248.74	69184.85
Jul	257.84	71616.00
Aug	257.87	77519.15
Sep	256.98	62185.22
Oct	247.15	50971.54
Nov	197.30	40945.80
Dec	181.93	33230.08

A first order SA is conducted to identify the factor that has the most significant impact on peak demand and total energy consumption of the office building. The dependency of the peak demand on the chosen variables can best be shown through the resulting distribution of outcomes as a function of the possible variation of input variables. Table 4.7 lists the building parameters, which are assumed to have a value randomly selected from a uniform distribution between a min and max value as given in the table.

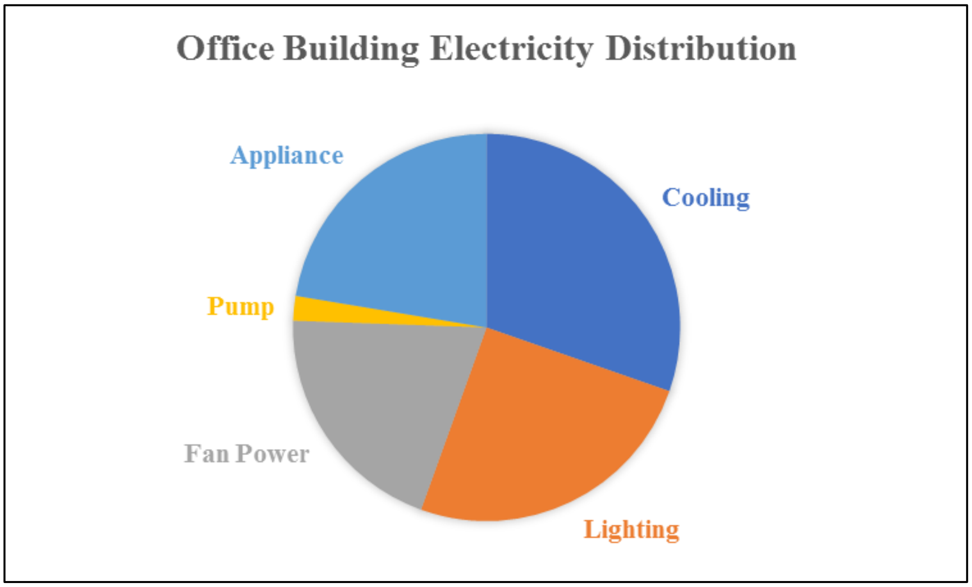


Figure 4.2 Categorical distribution of electricity usage in the office building

As introduced before, strategies that reduce demand charges are categorized into three types: energy efficiency intervention, flexible building load control, and renewable energy. In energy efficiency interventions, five parameters are considered as input variables that will impact the peak power, coincident peak power and total energy consumption of the building.

Infiltration or air leakage refers to the unintentional or accidental introduction of outside air into a building. The range of infiltration rate is from 0.2 $m^3/h/m^2$ to 0.8 $m^3/h/m^2$ (EN 15242). The total cost of caulking a typical office building includes labor fees of caulking at the window trim, door trim, area preparation, and protection, as well as the materials fees. The total cost of caulking ranges from $400 to $1,000 every 100 m depending on the quality of the work (RS Means 2017).

Table 4.7 List of optimal variables

	Building Parameters	Value		Cost
		Min	Max	
Energy Efficiency Intervention	Infiltration Rate ($m^3/h/m^2$)	0.2	0.8	$4-$10/m
	Wall Insulation Thickness (mm)	0	100	$10-$17/m^2
	Emissivity of Roof	0.4	0.9	$10-$22/m^2
	Solar Reduction Factor	0.8	1	$45-$65/each window
	Window SHGC	0.25	0.8	$450-$650/each window
Flexible Building Load Control	Temperature Control (℃)	0	2.5	Productivity lost
	Lighting Dimmer	0	30	$300/each dimmer
	Voltage Throttling	0	1	Productivity lost
Renewable Energy	Area of the PV System (m^2)	0	200	$520 per m^2

Insulating the exterior opaque envelope of the building reduces transmission losses and gains. It is a typical EEM in the building retrofit project. The typical range for the thickness of the wall insulation layer is 0 mm to 100 mm. The cost to install a typical batt insulation layer includes labor fees of fitting and securing batt insulation between open wall joists, preparation, and cleanup, as well as the materials fees. The total cost of installing wall insulation ranges from $1,000 to $1,700 every 100 m^2 (RS Means 2017).

The emissivity of the roof refers to the ability of the surface material on the roof to re-radiate the absorbed solar radiation back to the sky, which relates to the amount of total heat that is emitted by the roof material after the heat is absorbed. The emissivity of roof is measured on a scale ranged from 0 to 1. The closer the value is to 1, the higher the emissivity and more emitted heat to the colder night sky the roof can emit heat. Most (untreated) roofs have an emissivity ranged from 0.8 to 0.9, which implies that the emissivity to the colder sky through long wave radiation is unsuppressed. The more important parameter of the roof surface is its absorptance of shortwave radiation from the sun. Color plays a major role in the reflective properties of the roof. The typical range for the reflectivity of the roof is from 0.4 to 0.9. Values lower than 0.6 can only be achieved with special white coatings, and they only perform well over time if the roof surface is kept clean. With enough regular rainfall, no other cleaning is typically necessary. The cost to change a “dark” roof to a white roof includes labor fees of removing previous paint, brushing paint, and adding the waterproof layer, as well as the materials fees. The total cost of painting a roof white ranges from \$1,000 to \$2,200 for every 100 m^2 (RS Means 2017).

The solar reduction factor of the window represents the permanent installation shading devices outside or curtains inside the windows, which reduce the direct and indirect transmission of solar radiation into the building (ISO 13790 Annex G.5.2). The typical range of the solar reduction factor of white curtains inside the window is from 0.6 to 1. The closer the value is to 0, the higher reduction of the global transmission of solar radiation and the better thermal performance of the curtain. The cost to install a curtain on a typical window includes labor fees of punching holes on the wall, hanging the curtain, and the cost of materials.The total cost of installing a white curtain ranges from \$45 to \$65 each window (RS Means 2017).

The SHGC of the window is defined as the fraction of incident solar radiation that enters the interior space through the window in the form of direct radiation, and the absorbed heat from the window and internal shades (an indirect result of radiation). The procedure for testing window products and assigning SHGC ratings is performed by the National Fenestration Rating Council (NFRC), which was first started in 1993. Solar heat gain through the window is a significant factor that will impact the cooling load in commercial buildings. SHGC of glazing ranges from 0.25, for highly reflective coatings on tinted glazing with double layers, to 0.8, for uncoated water-white clear glass with a single layer. The closer the value is to 0, the higher reduction of the incident solar radiation that passes through the window, and the better thermal performance of the window. The cost of replacement of existing window includes labor fees for removing and disposing of old windows, installing replacement windows, and the cost of materials. The total cost of replacing a window ranges from $400 to $650, depending on the physical property of the window (RS Means 2017).

In the flexible building load control, three parameters are considered as input variables that will impact the peak power, coincident peak power, and total energy consumption of the building.

Temperature control of the building refers to the setting of thermostats that can be adjusted toward the comfort threshold value instead of the optimal desired value (at 25℃ instead of 22℃, for example) from 12 p.m. to 4 p.m. in summer months to reduce coincident peak. The range of the temperature control float is from 0℃ to 2.5℃. The cost of the temperature control is estimated based on annual productivity loss of the people inside the building.

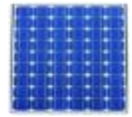
A lighting dimmer installed in the lighting system can be used to control lights in certain areas of the building from 12 p.m. to 4 p.m. in summer months to reduce the coincident peak demand. The number of lighting dimmers in the building ranges from 0 to 30. The cost of installing a lighting dimmer includes the material and labor fees, which ranges from $200 to $300.

Voltage throttling, with voltage-reduction controllers, could effectively lower the coincident peak demand and energy usage over time, through regulating the voltage output of high power-consuming equipment, i.e. chillers. In the optimization space, the voltage throttling is a binary parameter, that the user could determine whether or not to install an active voltage controller. The voltage throttling is realized by implementing a 20% capacity reduction on the chiller in our case studies. The cost of the voltage throttling is calculated based on the annual productivity loss of people inside the building in the case that a temperature increase is the result of the voltage reduction. Other cost factors associated with voltage reduction such as potential damage to equipment, added maintenance or shorter equipment service life are not considered at this stage of analysis.

It is worth mentioning that all the three EFMs introduced in this thesis are considered as static building control strategy, which is applied to all days during the year. In reality, the EFM should be based on a dynamic signal sent from the utility or model predictive control. This thesis treats the dynamic control decisions as a "design decision" i.e. designed as a fixed protocol. The reason is that we want to explore the inclusion of the measure as a design decision that will be applied irrespective of the need for peak load reduction on a given day, such as the day that in the expectation will be a peak load day. In other words, our focus at this stage is only on whether implementing a certain EFM in the building based on a fixed daily schedule will be among the optimal set of designed measures. It is to be expected that such a "design-EFM" will penalize heavily because of its indiscriminate daily application. The next stage is then to add dynamics to such an EFM which will make it more likely to be among the optimal set. The dynamic application of EFMs will be dealt with in follow-up work.

In renewable energy, installing a PV system is considered as an optimization parameter that impacts the peak demand, coincident peak demand and total energy consumption of the building. A rooftop PV system can generate electricity during a clear day with sufficient solar radiation. The total area of the PV array in the case building ranges from 0 m^2 to 200 m^2, which is limited to the size of the roof area. Table 4.8 details the cost analysis of a typical PV system.

Table 4.8 Cost information of the PV system

PV Generator Solar Module		
SunPower SPR-245NE Mono-c-Si PV module Efficiency: 19.7% Maxiimum Power Output: 245 Wdc		$100/m^2
Support Structure (Mounting Frame)		
DynoRaxx Evolution FR System: -Baskets (Fiberglass) – 1.7 baskets/PV module -Rails (Fiberglass) – 2.1 rails/PV module -Clamps (Stainless Steel) – 3.5 clamps/PV module -Dyno Pins – 4.2 pins/PV module		
Inverter		
SunPower Corp (Original Mfg): SPR-5200 240V AC Voltage: 240V Power Aco: 5,200 Wac Power Dco: 5,384 Wdc		$420/m^2
Monitoring System		
Monitoring System for PV installation		
Feed-in meter		
Feed-in meter for PV installation		
DC/AC Cabling		
Draka cables for connection between the solar panels and the inverters		

In the first step, a range analysis and sensitivity analysis (SA) of the billing demand of the building is conducted. Figure 4.3 shows the range or distribution of the peak demand as the result of varying the EEM/EFM parameters within their given range based on the choice of measures, which illustrates that the billing demand can be reduced to 200 kW with the proposed measures, i.e. there are a few (approximately 2%) realizations of measures that will lead to a demand below 200 kW.

Figure 4.4 and Figure 4.5 rank the significance of each parameter in the resulting peak load distribution based on the change in output mean and regression coefficient. The result is shown in a customary tornado plot, which can be interpreted as follows. Tornado diagrams are useful for deterministic SA in terms of comparing the relative importance of variables. For each variable considered, the range of the outcome will be estimated through multiple repeatable simulations with the randomly selected value from the variable space. The sensitive variable is modeled as an uncertain value while all other variables are held at stable values. In this case, a decision maker needs to visually compare nine measures to reduce demand charges and come to the conclusion that the main focus should be on roughly four dominant factors. In a regression coefficient diagram, the top four bars represent variables that contribute the most to the variability of the outcome and therefore on what the building owner should focus. The top four factors that have the most significant impact on the billing demand are found to be: the SHGC of the window, the solar reduction factor, the temperature control, and the PV area. The SHGC of the window and the solar reduction factor rank the first and second most influential parameter. This is caused by the fact that Atlanta has strong solar radiation in the summer season, especially during noon hours, and the building has a 50% window-to-wall ratio on the east and west façade. Therefore, the window SHGC and the solar reduction factor can reduce the solar load the most and have the highest impact on the peak demand.

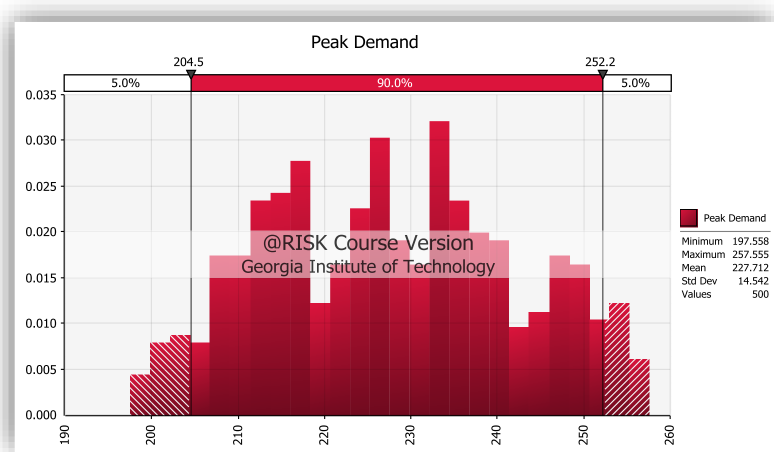


Figure 4.3 Distribution of the peak demand

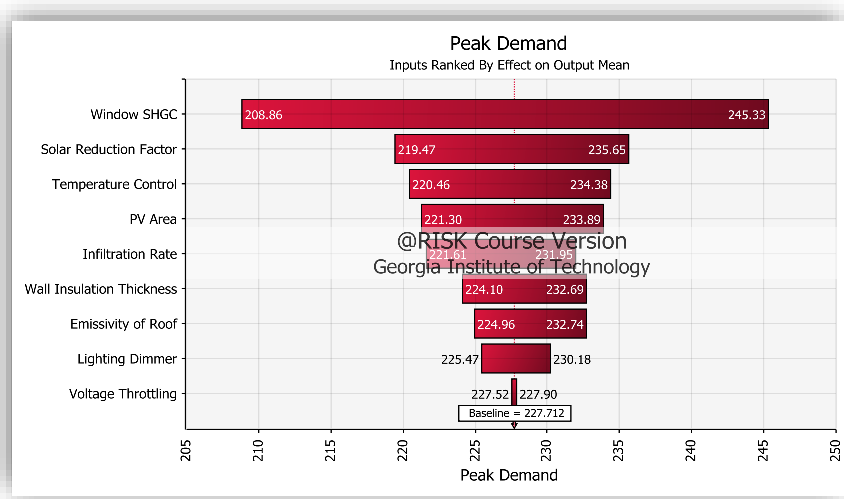


Figure 4.4 SA ranking based on the change in output mean

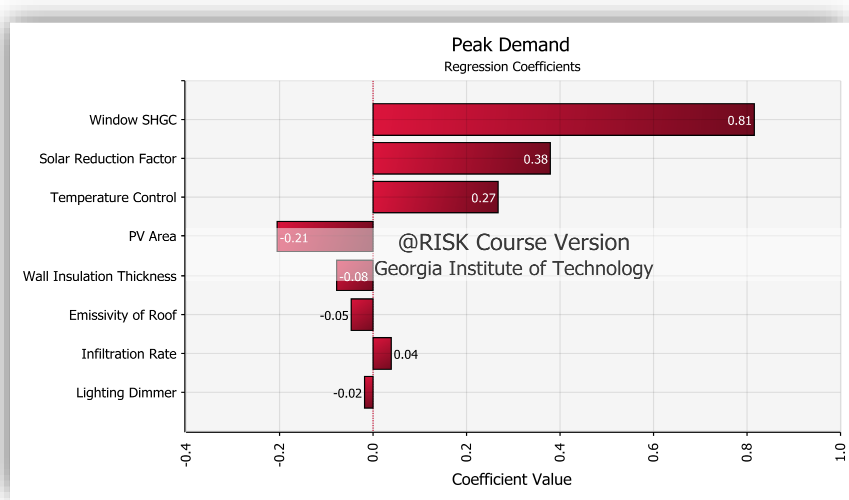


Figure 4.5 SA ranking based on regression coefficient

The second step of the SA is carried out on the coincident peak demand of the building. Figure 4.6 illustrates the distribution of the coincident peak demand as the result of varying EEM and EFM parameters, which implies that the coincident peak demand in the building can be reduced to roughly 140 kW with the proposed optimization factors, with the most extreme reduction being 134 kW. Figure 4.7 and Figure 4.8 rank the significance of each parameter in the resulting coincident peak load distribution based on the change in the output mean and the regression coefficient. The top three factors that have the most significant impact on the coincident peak demand are the temperature control, the window SHGC, and the area of the PV system. The temperature control ranks as the most significant factor. This is due to the fact that the temperature setpoint is temporarily increased during the summer peak hours, which brings down the coincident peak demand. The area of the PV system ranks as the third significant factor. PV generation, to some extent, is correlated to the coincident peak, because the increased solar radiation is one of the main reason that the building load increases. By producing more power during peak hours with the most amount of solar radiation during the day, installing a PV system is recognized as one of the most effective measures that could decrease the coincident peak demand by increasing the load flexibility of the building.

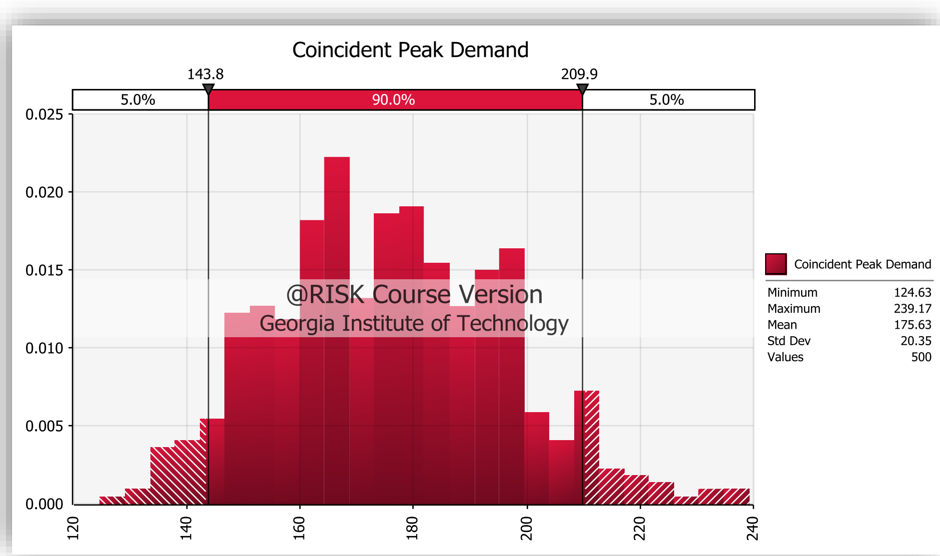


Figure 4.6 Distribution of the coincident peak demand

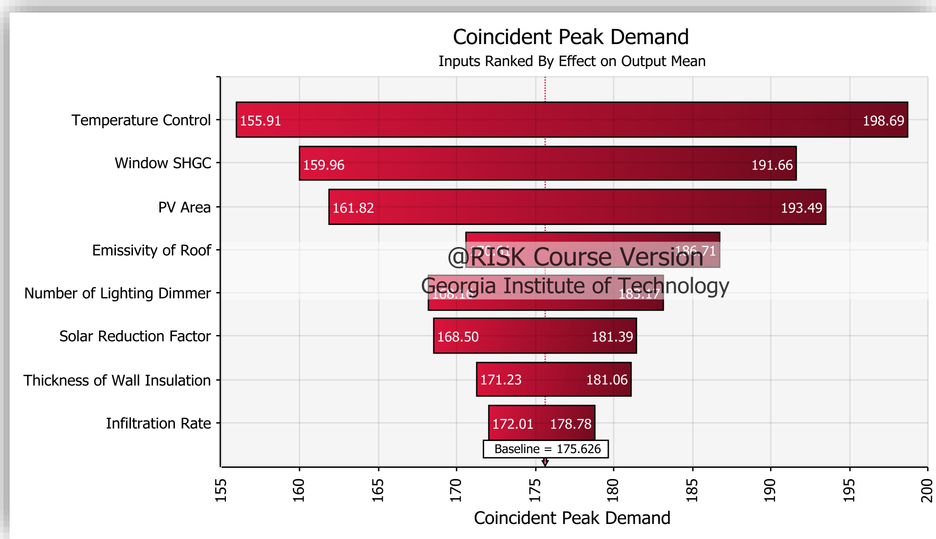


Figure 4.7 SA ranking based on the change in output mean

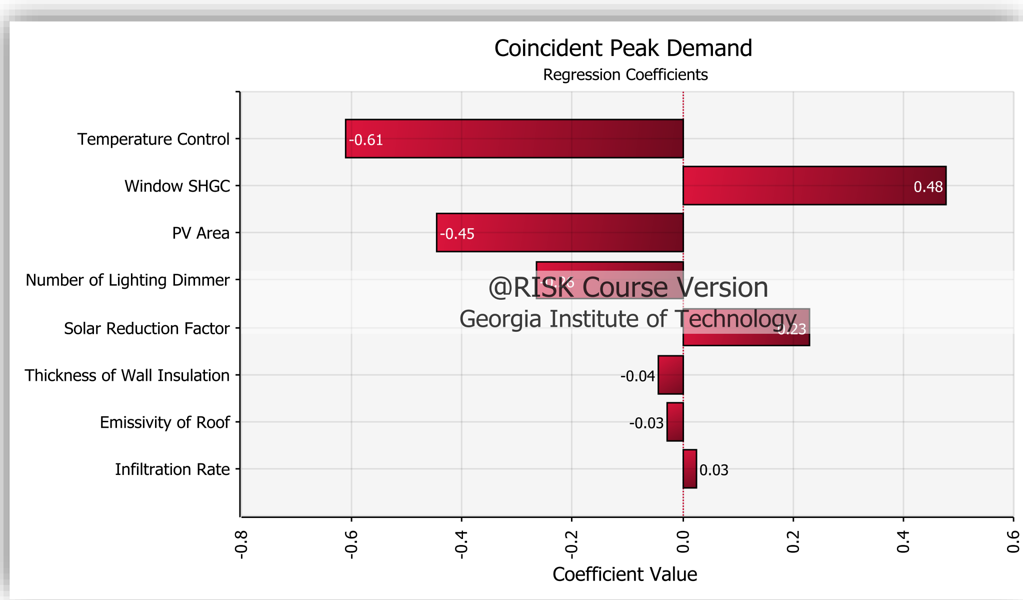


Figure 4.8 SA ranking based on regression coefficient

The last step of the SA is implemented on the total energy consumption of the building. Figure 4.9 shows the distribution of the total energy consumption as the result of varying the parameters that characterize the EEM and EFM. The range of the distribution implies that the total energy consumption in the building can be reduced to 48,000 kWh with the proposed measure. Figure 4.10 and Figure 4.11 rank the role of each parameter in the resulting total energy consumption distribution based on the change in output mean and regression coefficient. PV area ranks as the top significant impact parameter. Window SHGC and solar reduction factor rank as the second and third most influential parameter. Temperature control that ranks third most significant factor in the SA study of peak demand and coincident peak demand does not show a significant impact on the total energy consumption, which is because temporarily increasing the temperature is merely a load shifting strategy that shifts part of the load to off-peak hours.

The results of the SA based on regression coefficient show that infiltration has a negative impact on the total energy consumption of the building, which implies that sealing the building better will actually increase the annual energy consumption and peak demand. Infiltration in the building can bring in extensive heating load in winter and cooling load in summer. However, the result in the case study suggests that utilizing infiltration can help reduce the cooling load of the core zone of the building during the winter season and cooling down the building in early morning and night time during the summer season. The energy savings of night cool down in summer and winter cooling exceed the cost of increased heating load in the winter season. Therefore, better sealing a building does not always bring down the energy costs. In certain climate zones during certain periods, the building could, in fact, rely on natural ventilation for cooling. The same conclusion could be applied to the insulation of the building. Better insulation can decrease the positive effect of losses to the outside during cooling times of the day. Generally, in hot climate zones, buildings with relatively high heat gain (solar and other) can have higher cooling loads with decreasing infiltration and higher insulation. This trend is seen in many commercial buildings with a relatively high internal gain, resulting in a net cooling demand for most months of the year.

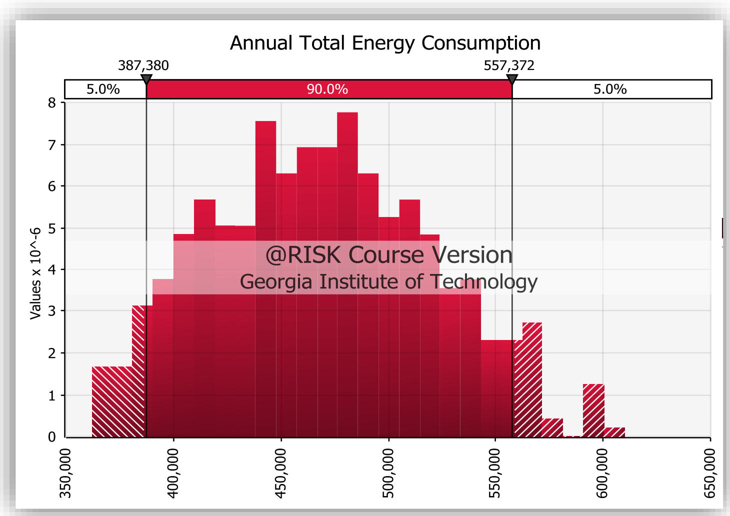


Figure 4.9 Distribution of the total energy consumption

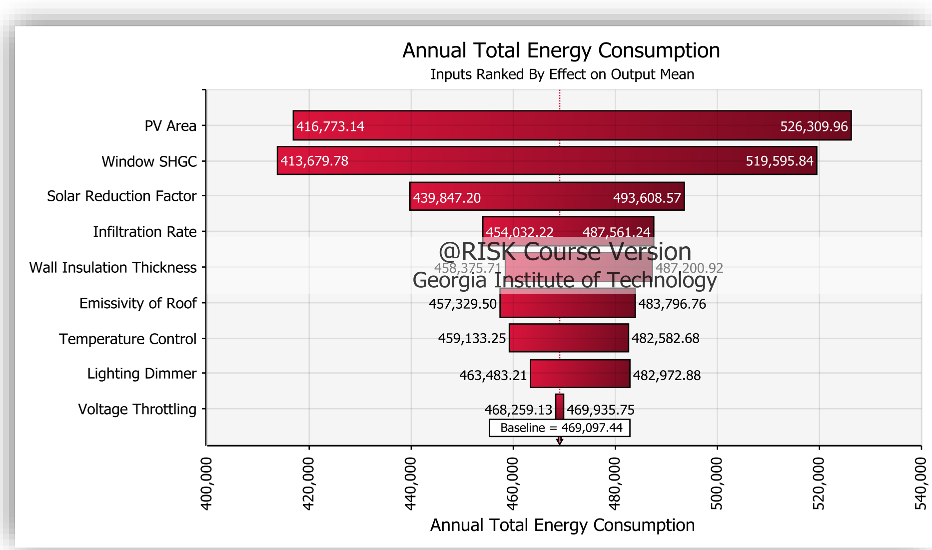


Figure 4.10 SA ranking based on the change in output mean

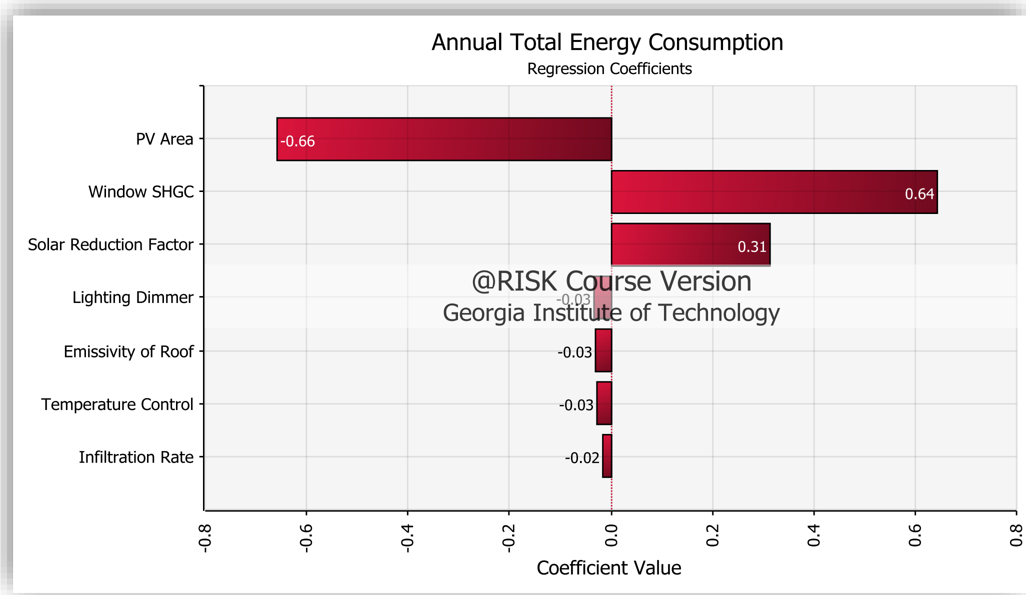


Figure 4.11 SA ranking based on regression coefficient

The interpretation of the SA needs to be done with care. In fact, it is only a limited way to interpret the effect of parameters in the outcomes. It is important to note that the sensitivity index outcomes depend on the range within which each design variables varies. In particular, if the upper limit or the lower limit of a factor is extended, its contribution to the output variance may increase while the contribution of the other design variables decreases as a consequence. On the total energy consumption, the PV area ranks as the most significant factor. The range of the applicable PV area is obviously a dominant factor in this. For a smaller roof area, it will be found that PV is no longer the dominant parameter. It must be well understood that results obtained in the SA studies above, pertaining to the total variance of peak demand, coincident peak demand, and total energy consumption and ranking of most influential parameters, are very dependent on the definition of the ranges of the EEM and EFM variables. If the ranges were shortened, it would be possible to see a reduction in the sensitivity as well as a different ranking of the parameters.

The next sessions will show the financial analysis and cost optimization of EEM/EFM for the office building under different rate structures.

4.1.2 Case 1: Georgia Power PLM-11

This case adopts the GP's schedule PLM-11 to calculate the cost of electricity and to evaluate the optimal combination of EFMs to reduce demand charges. The case building's peak demand is 257.78 kW, which is difficult to reduce below 30 kW. Therefore, for the case building, demand charges are linearly correlated to the peak demand value in each month under the PLM-11.

Georgia Power's Power & Light tariffs (PL-Small, PL-Medium, and PL-Large) adopt the HUD structure, which charges customers based on their total energy consumption as well as usage frequency (Georgia Power PLL). HUD indicates how consistently a customer is using electricity during the billing month. The higher the HUD, the more hours the customer is operating and usually the lower their unit (kWh) cost. HUD determines how a customer is billed under the appropriate Power & Light tariff. The calculation for HUD is:

$$\mathrm{HUD} = \text{Monthly total energy consumption (kWh)}/\text{Billing demand (kW)}$$

The first step is to calculate the monthly electricity cost. Taking the summer month August as an example, the first part is to determine the peak demand in the current month. According to Table 4.6, the peak power in the current month is 257.87 kW. According to PLM-11, this value is higher than the 95% of the highest peak demand in summer months and 60% peak power in winter months, the billing demand power in August is 257.87 kW. The second part is to calculate the HUD in August.

$$\mathrm{HUD} = 77519(\mathrm{kWh})/258\ (\mathrm{kW}) = 300$$

The HUD in August is higher than 200 hours but less than 400 hours. According to Appendix A, the electricity price is $0.011437 per kWh. Table 4.9 illustrates the steps to calculate the monthly electricity bill in August.

Table 4.9 Calculation of the monthly electricity bill

Customer Charges	1 month	@	$19.00	$19.00
Demand Charges	257.87 kW	@	$8.24	$2,124.85
Energy Charges	77,519.15 kWh	@	$0.01143	$886.04
Subtotal				$3,029.89
ECCR Charges	$3,029.89	@	0.100131	$303.39
NCCR Charges	$3,029.89	@	0.075821	$229.73
FCR Charges	77,519.15 kWh	@	$0.03258	$2,525.88
Subtotal				$6,088.89
MFF Charges	$6,088.89	@	0.029109	$177.24
Subtotal				$6,266.13
Sales Tax	$6,266.13	@	7%	$438.63
Total Electric Charges				**$6,704.76**

In GP PLM-11, Environmental Compliance Cost Recovery (ECCR) charges recover the costs of installing and operating environmental controls mandated by the government. Nuclear Construction Cost Recovery (NCCR) charges recover financing costs related to the construction of two new nuclear units at Plant Vogtle near Waynesboro, GA. Fuel Cost Recovery (FCR) fee recovers fuel and environmental cost. Municipal Franchise Fees (MFF) recover the payment to cities for allowing GP to conduct business within the city limits and on the cities' rights-of-way. The total amount to be paid by the building is $6704.76. The result reveals that the total energy charge is only 10% of the total bill, while the demand charge is almost 30% of the total bill.

The next step is to determine the cost-optimal selection of EEM at each of the five distinct budget levels introduced before. The first level is the baseline building with zero EEM budget. In each of the following budgets, there is a $50,000 increment in the capital EEM funding compared to the previous one, and at the highest level, the initial EEM budget reaches $200,000 (which is the maximum possible investment in EEM for this building). The next step is to determine the optimal investment in EFMs for the five distinct EEM budget levels introduced before.

The optimal combination of EFMs is determined by maximizing the NPV over a 20-year period. The intent of separating EFMs from EEMs in the optimization analysis is to find how much demand charge reduction through EFMs is impacted by the level of EEM budget and its associated accomplished energy efficiency in the building. Moreover, we gain insight in the demand charge reduction potential of EFMs. The two steps are implemented as follows:

Step 1: find optimum EEM for the chosen budget level. This is done by finding the optimal set of EEM that fits exactly within the specified budget. The budget is not using an upper constraint but it is the fixed amount to be spent on EEM.

Step 2: with the fixed EEM results of step 1, find the optimum mix of EFM that can be added; this is done by finding the EFM mix that achieves maximum NPV over 20 years.

The results of the analysis are shown in the graphs below. The interpretation of the charts below and throughout this analysis needs to be done with care. Each graph shows the five distinct budget levels along the horizontal axis (1 to 5). The red line corresponds to the legend on the left, showing the investment in the technologies and measures. For the EEM investment, this is exactly equal to the given budget as explained. The green line shows the demand charge savings that can be obtained by choosing the EEM or EFM or both at the 5 budget levels, using the green legend on the right.

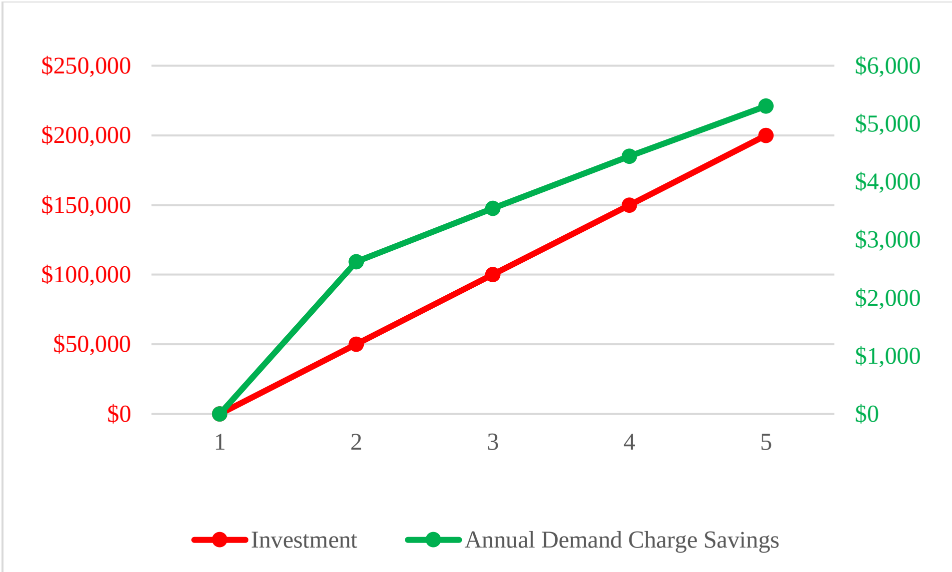


Figure 4.12 Investment and demand charge savings of EEMs

Figure 4.12 displays demand charge savings as the result of implementing EEMs at the five budget levels. The red curve represents the investment and the green curve corresponds to annual demand charge savings of EEM. Both curves go upward which can be expected. The figure cannot be used to determine the optimum investment case although it can be seen that the first 50,000 of the budget has the highest relative return (steepest ascent in the green curve) when only considering demand charge reduction. As the investment also generates revenues from energy consumption reduction, the optimum investment may occur at a different budget level. An NPV study is therefore performed below.

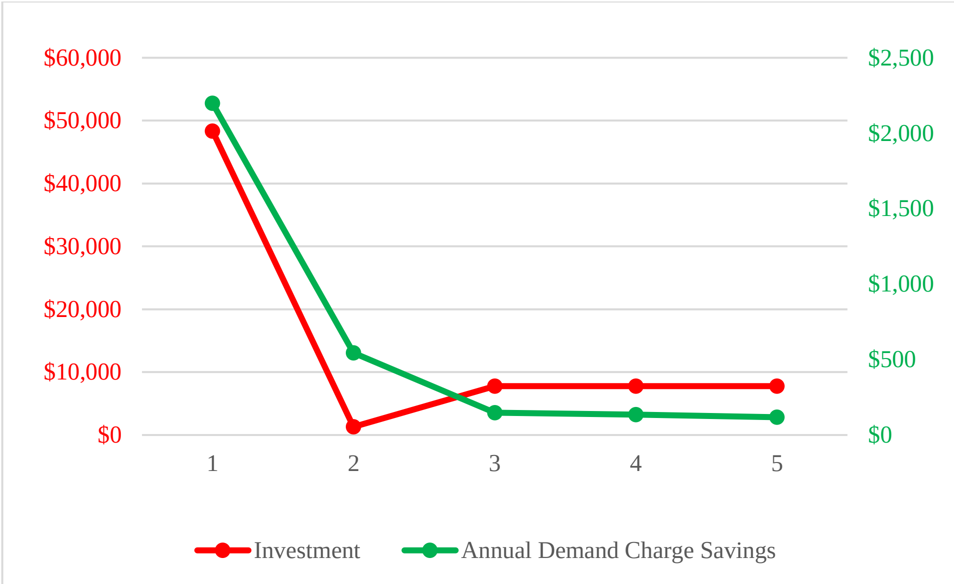


Figure 4.13 Investment and demand charge savings of EFMs

Figure 4.13 shows the investment in EFM at the five EEM budget levels, with the resulting demand charge savings. The red curve represents the investment, which drops sharply at budget 2. Budgets 3, 4 and 5 have the same costs, which are higher than those at budget 2. The green curve corresponds to demand charge savings, which shows a downward trend from budget 1 to 5. It is notable that the building operator spends the same amount of money on EFMs at budgets 3, 4 and 5, however, the demand charge savings slowly decline as the EEM budget increases. This is not surprising as in general, we expect that the potential of demand charge savings through EFMs is impacted by energy efficiency of the building. As more budget is allocated to enhance energy efficiency features, the space for demand charge reduction through improving energy flexibility in buildings is compressed, and only the "cheap" EFM make sense for high energy efficient buildings.

Figure 4.14 illustrates the total investment (for EEM and EFM combined) and demand charge savings. This is basically a combination of the previous two figures. The result suggests that budget 2 has the maximum efficiency of investment in demand charge savings.

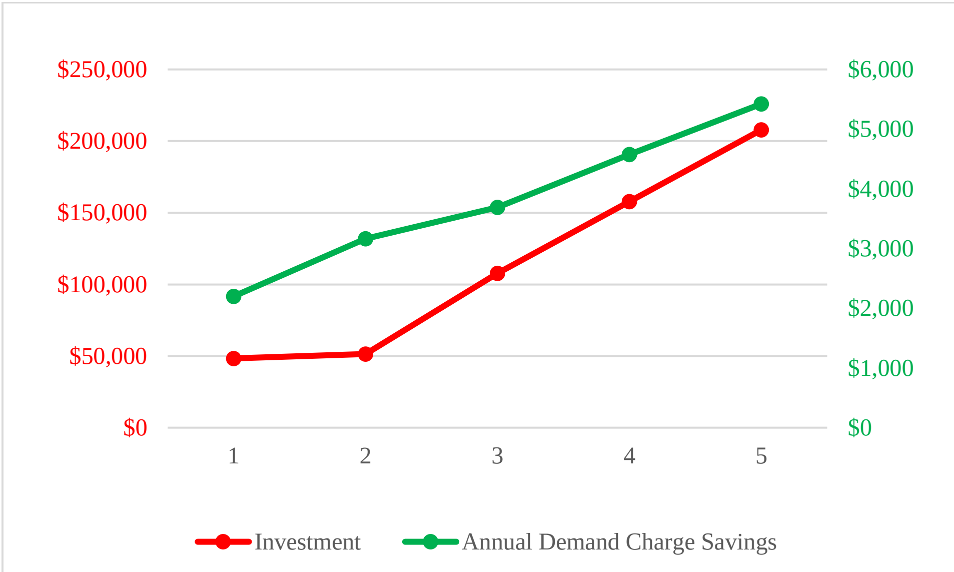


Figure 4.14 Investment and demand charge savings of combined EEM+EFM

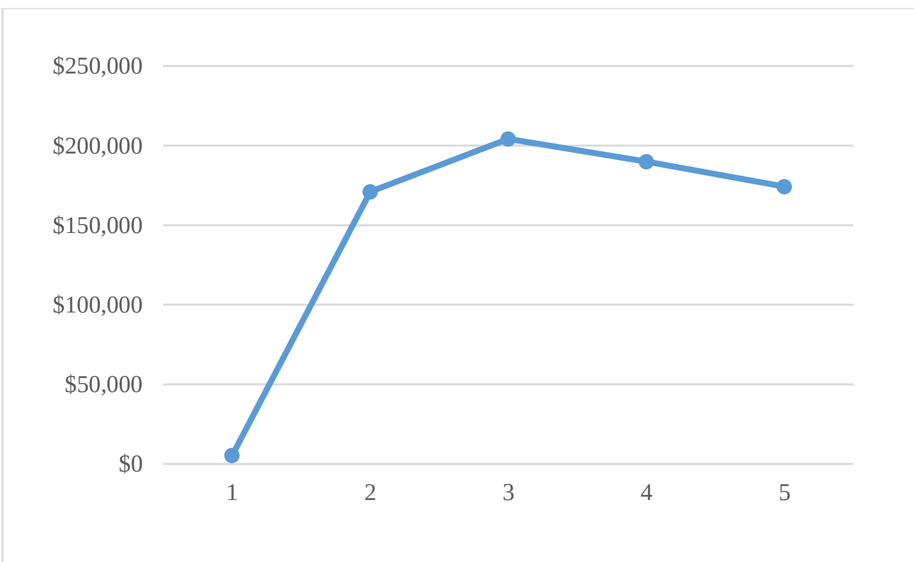


Figure 4.15 NPV results of combined EEM and EFM

The NPV results displayed in Figure 4.15 imply that the optimal investment strategy at budget 3 has the maximum investment payback over twenty years. If the case building user wants to achieve maximum investment gains in a twenty-year period, they should choose the optimal investment strategy suggested at budget 3. If they pursue the fastest payback of the investment in demand charge reduction, they should choose the optimal investment strategy suggested at budget 2 as suggested by Figure 4.14.

4.1.3 Case 2: Pacific Gas & Electricity A-10 Non-TOU

This case adopts the PG&E's schedule A-10 non-TOU rates to calculate the cost of electricity and to evaluate the best measure and investment strategy to reduce demand charges. The case building's peak demand is 258 kW. If the end user successfully attempts to reduce the peak demand below 200 kW, they could switch to schedule A-1 for small general service, which has the same energy rate as A-10, but no demand charge. Therefore, if the results show that demand charges contribute a lot in the electricity bill, the end user should make a serious effort to bring the peak demand below 200 kW.

The first step is to calculate the monthly electricity bill. Taking the summer month August as an example, the first part is to decide the peak demand in the current month. The customer will be billed for demand according to the customer's maximum demand, which equals to the highest 15-minute average in the month. According to Table 4.6, the billing demand in August is 257.87 kW. Appendix B lists the rate structure of schedule A-10 non-TOU rate. Table 4.10 details the steps to calculate the monthly electricity bill in August.

Public Purpose Programs is used to fund state-mandated gas assistance programs for low-income customers, energy efficiency programs, and public-interest research and development.

Nuclear decommissioning recovers financial cost for decommissioning of a nuclear power plant when it reaches the end of its useful life in the U.S. This charge is directly deposited in a trust fund, and do not belong to the utility company. Competition Transition Charges is collected to pay down stranded costs incurred as a result of the transition from a regulated market to a deregulated one. Department of Water Resources (DWR) bound recovers fees for DWR procuring electricity on behalf of the three investor-owned utilities in January 2001, during the California energy crisis. New System Generation Charge covers the cost of adopting new systems to produce electricity. The total amount to be paid by the building in August is $18,462.72. The result reveals that the demand charge is 20% of the total bill.

Table 4.10 Calculation of the monthly electricity bill

Customer Charge	31 days	@	$4.60	$142.59
Demand Charges	257.87 kW	@	$16.78	$4,327.06
Energy Charges	77,519.15 kWh	@	$0.14	$10,518.57
Transmission Rate Adjustments	77,519.15 kWh	@	$0.00472	$365.89
Public Purpose Programs	77,519.15 kWh	@	$0.01416	$1,097.67
Nuclear Decommissioning	77,519.15 kWh	@	$0.00149	$115.50
Competition Transition Charges	77,519.15 kWh	@	$0.00100	$77.52
DWR Bond	77,519.15 kWh	@	$0.00549	$425.58
New System Generation Charge	77,519.15 kWh	@	$0.00238	$184.50
Subtotal				$17,254.88
Sales Tax	$17,254.88	@	7%	$1,207.84
Total Electric Charges				$18,462.72

The next step is to determine the optimal investment in EFMs for the five distinct EEM budget levels, which are the same as described above.

Figure 4.16 displays demand charge savings and investments of implementing optimal EEMs. The red curve represents the investment at each budget level, and the green line corresponds to demand charge savings. Both curves go upward. Among five distinct budgets, budget 2 turns out to have the highest efficiency of investment, when only considering demand charges.

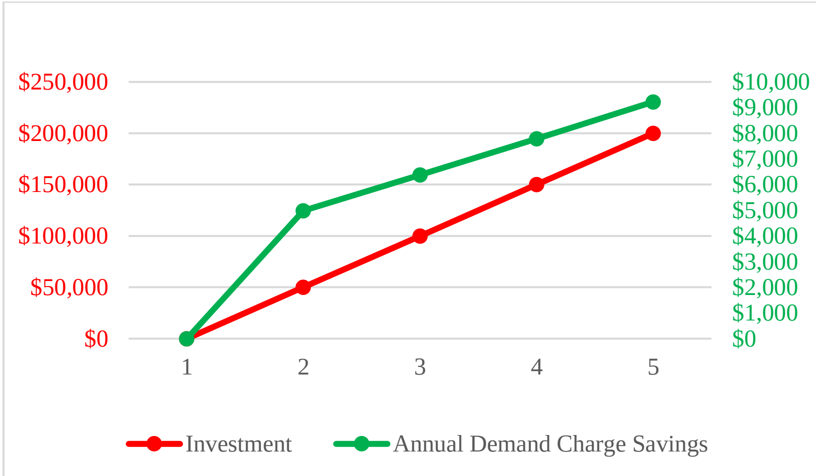


Figure 4.16 Investment and demand charge savings of EEMs

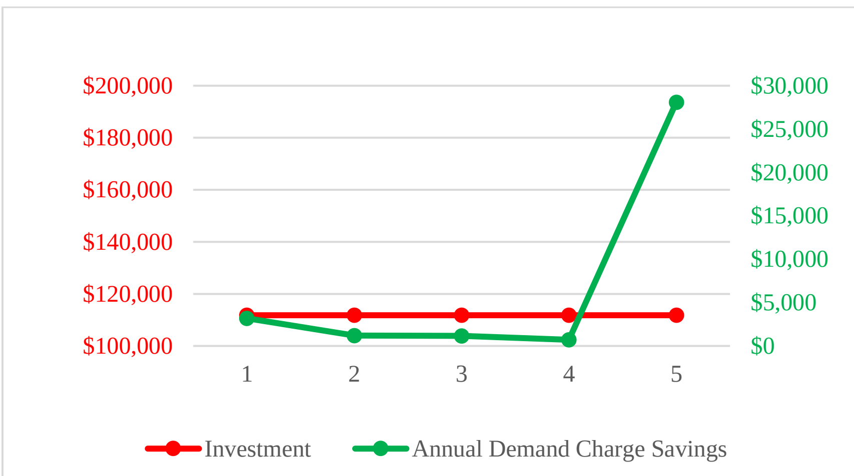


Figure 4.17 Investment and demand charge savings of EFMs

Figure 4.17 shows investments demand charge savings of implementing the optimal EFMs at each EEM budget level. It is found that optimal investment is identical at all budget levels. The annual demand charge savings decline from budget 1 to 4 because the increased budget on EEMs compresses the space of financial savings through EFMs. There is a steep rise at budget 5, which is due to the fact that executing EFMs for for this building with high energy efficiency will successfully bring the peak demand down below 200 kW, at which point no demand charge will be applied to the building This typical step change behavior is typical for this rate structure.

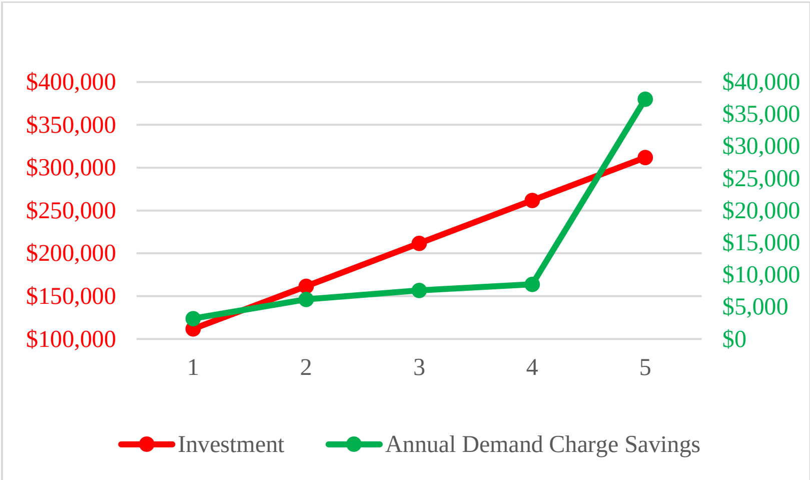


Figure 4.18 Investment and demand charge savings of combined EEM+EFM

Figure 4.18 depicts the change of total investment and demand charge savings. The sharp rise of demand charge savings at budget 5 is caused by the specific rate structure in PG&E. In PG&E, if the end user's peak demand is below 200 kW for three consecutive months, that customer will be transferred from the current schedule A-10 to schedule A-1, which has a higher energy charge but no demand charge. The user needs to trade off between the increment in energy cost and reduction in demand charges after implementing the optimal investment strategy.

The NPV results displayed in Figure 4.19 imply that the optimal investment strategy is at budget 5 which has the maximum investment payback over twenty years. The optimization result suggests that the financial benefit of reduced demand charges exceeds the rise in the energy price.

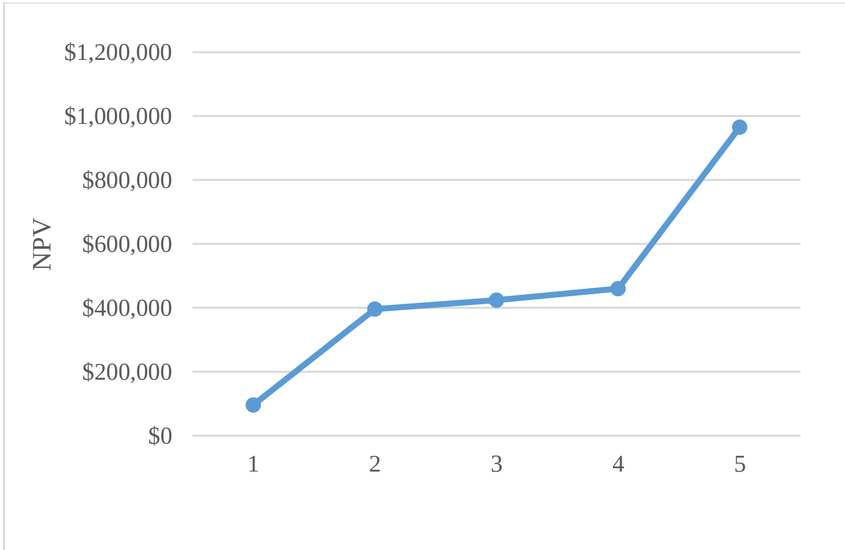


Figure 4.19 NPV results of combined EEM and EFM

4.1.4 Case 3: Pacific Gas & Electricity A-10 TOU

This case employs the PG&E's schedule A-10 TOU rates to calculate the cost of electricity and to evaluate the best measure and investment strategies to reduce demand charges. Different from the flat daily rate structure in case 2, the schedule A-10 TOU adopts a TOU rate structure. Table 2.1 and Table 4.3 details how times of the day are defined and how much is the hourly rate during a day. This rate schedule also includes the PDP rate, which is a DR pricing plan released to complement the TOU pricing. PDP provides lower energy prices during the summer in exchange for higher rates during certain hours on nine to fifteen peak event days per year. These event days can be triggered by forecasted high temperatures, high market prices, or California Independent System Operator emergencies. On these days, the cost of the electricity will increase during peak demand hours from 12 p.m. to 4 p.m. In a PDP event day, the customer will be charged $0.9 per kWh from 12 p.m. to 4 p.m. In contrast, they will receive a credit of $3.26 per kW reduction on peak demand in the month that contains the PDP event.

Table 4.11 Number of days meets the criteria

T>35.9 ℃	July 8
T>34.9 ℃	July 7, 14, August 1, 2, 18
T>33.9 ℃	June 6, 13, July 6, 9, 13, 21

The trigger of the PDP event is the outside temperature. If the maximum forecasted outside temperature of tomorrow is above 30℃, the utility company will dispatch PDP event calls. The total number of days that PDP event occurs should be between nine to fifteen. Building energy simulation software use the typical meteorological year (TMY) weather data, which is not the real weather but a collection of weather data from a data bank in 30-year duration that could well represent the range of weather phenomena for the location. For our analysis, the fifteen hottest days are chosen from the TMY weather file and used as the PDP event days. Table 4.11 lists the selection criteria and the dates of days that meet the criteria.

The first step is to calculate the monthly electricity bill. Taking the summer month August as an example, the first part is to decide the peak demand in the current month. The customer will be billed for demand according to the customer's maximum demand, which equals to the highest 15-minute average in the month. According to Table 4.6, the billing demand in August is 257.87 kW. Appendix C lists the rate structure of schedule A-10 TOU rate. Table 4.12 details the steps to calculate the monthly electricity bill in August. The total amount to be paid by the building in August is $24,486.72. It is worth mentioning that the rate structure in case 2 and 3 both apply to PG&E's customers with peak demand greater than 200 kW but less than 499 kW. The customer can choose which rate, TOU or non-TOU, they want to enroll in. TOU rate encourages people to improve energy flexibility by charging a higher rate during peak hours and a much lower rate during off-peak hours compared to the flat rate. Buildings with high energy flexibilities should choose TOU rate structure to enable them to save on energy bills by the proper operation. By comparing the monthly electricity charge in case 2 and 3, we find out that for the reference office building, before applying any EFM or EEM, choosing the non-TOU rate has a relative low electricity cost.

Table 4.12 Calculation of the monthly electricity bill

Customer Charge		31 days	@	$4.60	$142.59
Demand Charges		257.87 kW	@	$16.78	$4,327.06
Subtotal					$4,469.65
	On-Peak	30,314.67 kWh	@	$0.22	$6,660.74
	Partial-Peak	26,814.37 kWh	@	$0.16	$4,413.38
	Off-Peak	17,390.51 kWh	@	$0.14	$2,374.15
	PDP Events	2,999.60 kWh	@	$0.90	$2,699.65
Total Energy Charges		77,519.15 kWh			$16,147.92
Transmission Rate Adjustments		77,519.15 kWh	@	$0.00472	$365.89
Public Purpose Programs		77,519.15 kWh	@	$0.01416	$1,097.67
Nuclear Decommissioning		77,519.15 kWh	@	$0.00149	$115.50
Competition Transition Charges		77,519.15 kWh	@	$0.00100	$77.52
DWR Bond		77,519.15 kWh	@	$0.00549	$425.58
New System Generation Charge		77,519.15 kWh	@	$0.00238	$184.50
Subtotal					$22,884.23
Sales Tax		$22,884.23	@	7%	$1,601.90
Total Electric Charges					$24,486.12

The next step is to determine the optimal investment in EFMs for the 5 distinct budgets. Figure 4.20 shows demand charge savings and investments of implementing the optimal EFMs at each budget level. Both cost and saving curves go upward. Among five budgets, budget 2 turns out to have the highest efficiency of investment when only looking at demand charge savings.

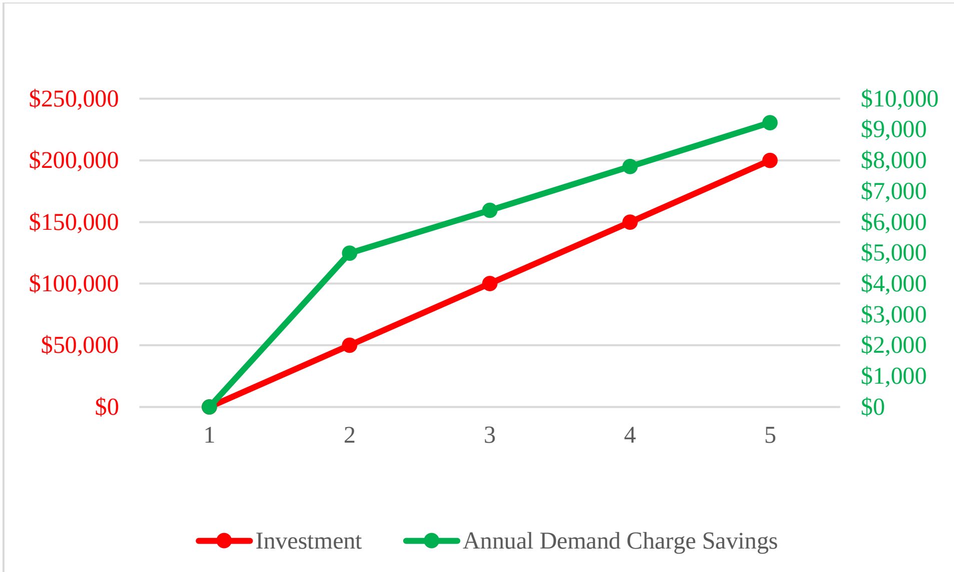


Figure 4.20 Investment and demand charge savings of EEMs

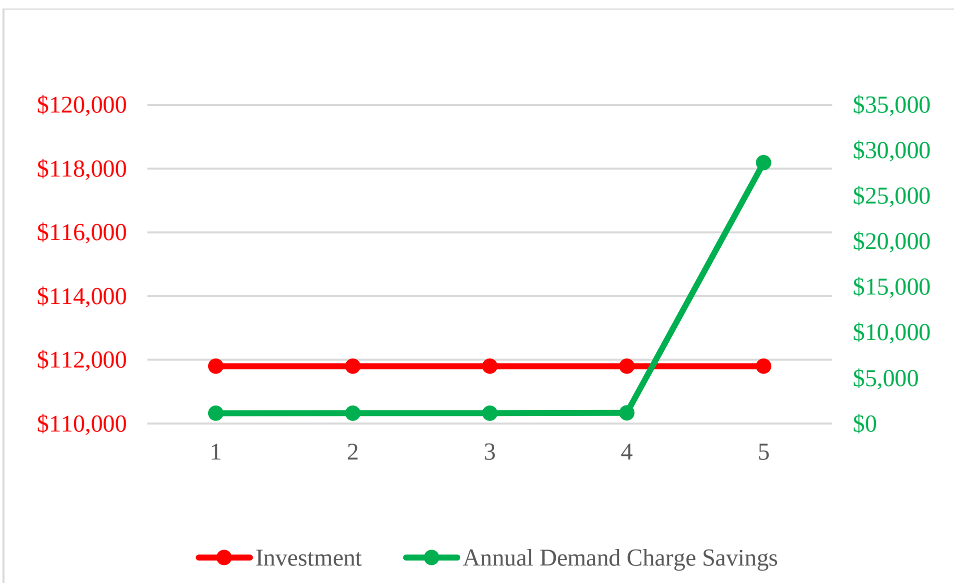


Figure 4.21 Investment and demand charge savings of EFMs

Figure 4.21 details demand charge savings and investments of implementing the optimal EFMs at each EEM budget level. The investment and demand charge saving curves remain the same for each budget, except a sharp rise at budget 5. This is because implementing EFMs with

EMMs at budget 5 can successfully bring the peak demand down below 200 kW, at which point no demand charge will be applied.

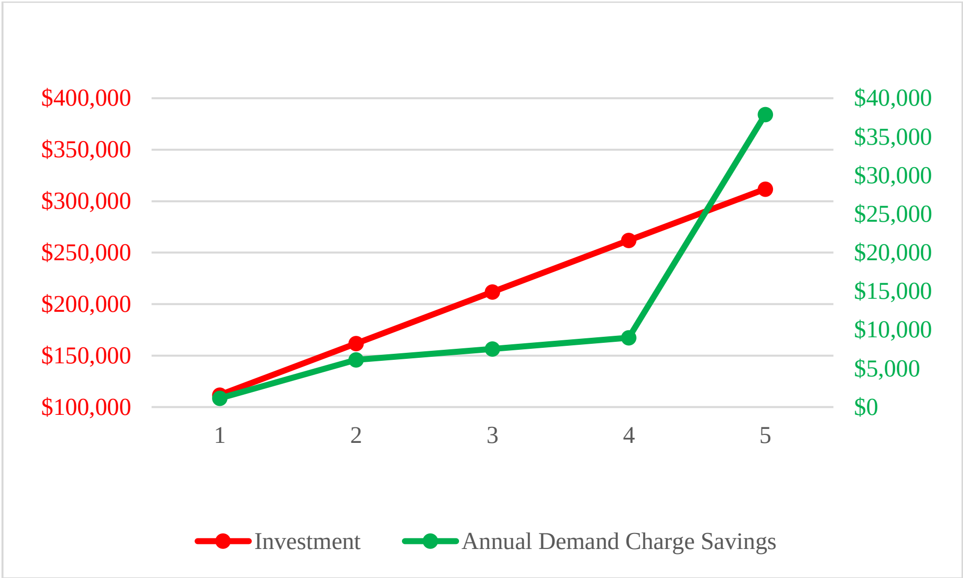


Figure 4.22 Investment and demand charge savings of combined EEM+EFM

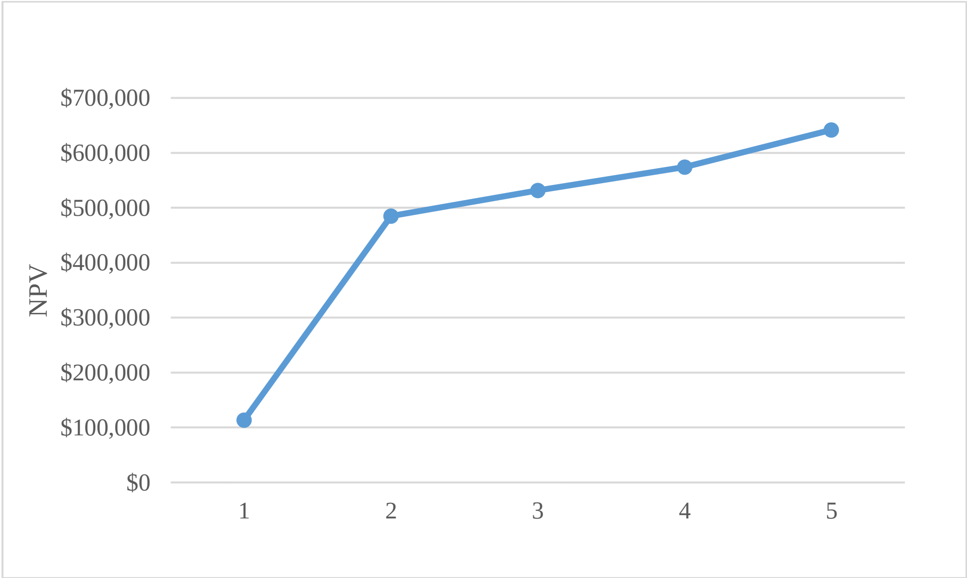


Figure 4.23 NPV results of combined EEM and EFM

Figure 4.22 depicts the change of total investment and demand charge savings. Among all the five budgets, budget 5 gains the highest demand charge savings. The NPV results displayed in

Figure 4.23 imply that the optimal investment strategy at budget 5 has the maximum investment payback over twenty years. Case 2 and 3 are different options of the same electricity rate structure that customers can choose from. In both cases, the optimization result suggests that the peak demand can reduce below 200 kW, which indicates that the financial benefit of reduced demand charges exceeds the rise in the energy price. By comparing the result of case 2 and 3, we could conclude that for the reference office building, the non-TOU rate has a higher NPV in twenty years compared to the TOU rate, which indicates that the energy flexibility level in the building is not high enough to earn benefit in the TOU rate.

4.1.5 Case 4: Southern California Edison TOU-GS-3 Option A

This case adopts the Southern California Edison's schedule TOU-GS-3 option A rates to calculate the cost of electricity and to evaluate the best measures and investment strategy to reduce demand charges. The case building's peak demand is 257.87 kW. If the end user successfully attempts to reduce the peak demand below 200 kW, they could switch to schedule TOU-GS-2 option A, which has a higher energy rate, but a lower demand charge. Therefore, if the results show that demand charges contribute a lot in the electricity bill, the end user should make a serious to bring the peak demand below 200 kW.

The first step is to calculate the monthly electricity bill. Taking the summer month August as an example, the first part is to decide the peak demand in the current month. The customer will be billed for demand according to the customer's maximum demand, which equals to the highest 15-minute average in the month. According to Table 4.6, the billing demand in August is 257.87 kW. Appendix F and H lists the rate structure of TOU-GS-3 option A and TOU-GS-2 option A.

Table 4.13 details the steps to calculate the monthly electricity bill in August. The total amount to be paid by the building in August is $24,486.72.

Table 4.13 Calculation of the monthly electricity bill

Customer Charge		1 month	@	$466.13	$466.13
Demand Charges		257.87 kW	@	$17.81	$4,592.66
Subtotal					$5,058.79
	On-Peak	30,314.67 kWh	@	$0.32	$9,589.74
	Partial-Peak	26,814.37 kWh	@	$0.11	$2,949.31
	Off-Peak	17,390.51 kWh	@	$0.06	$1,033.69
Total Energy Charges		77,519.15 kWh			$13,572.75
Subtotal					$18,631.54
Sales Tax		$18,631.54	@	7%	$1,304.21
Total Electric Charges					$19,935.74

The next step is to determine the optimal investment in EFMs for the five distinct budgets. Figure 4.24, Figure 4.25 and Figure 4.26 show demand charge savings and investments of implementing the optimal EEMs, EFMs and combined measures. The result from these analyses reveals that the optimal investment strategy for budget 5 achieves the maximum NPV in twenty years.

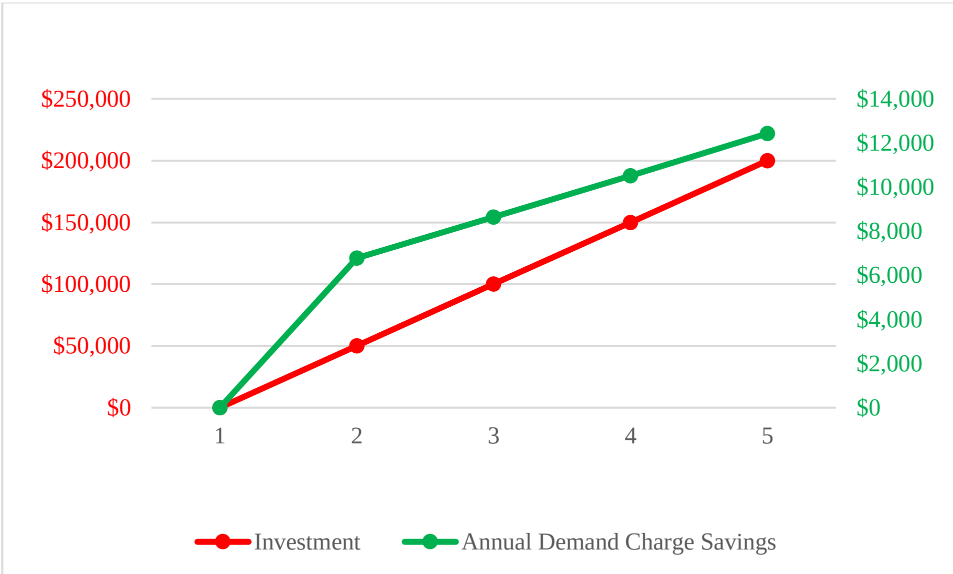


Figure 4.24 Investment and demand charge savings of EEMs

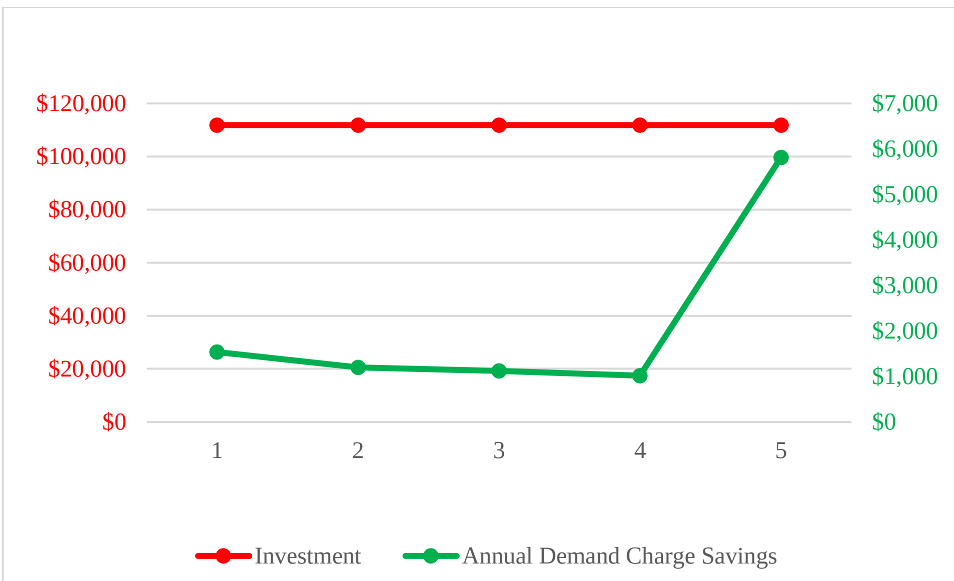


Figure 4.25 Investment and demand charge savings of EFMs

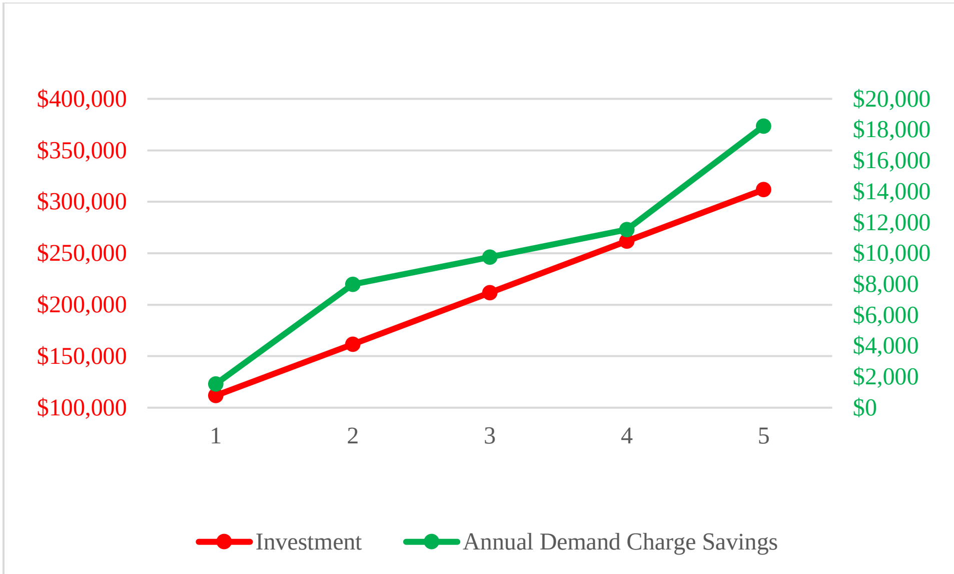


Figure 4.26 Investment and demand charge savings of combined EEM+EFM

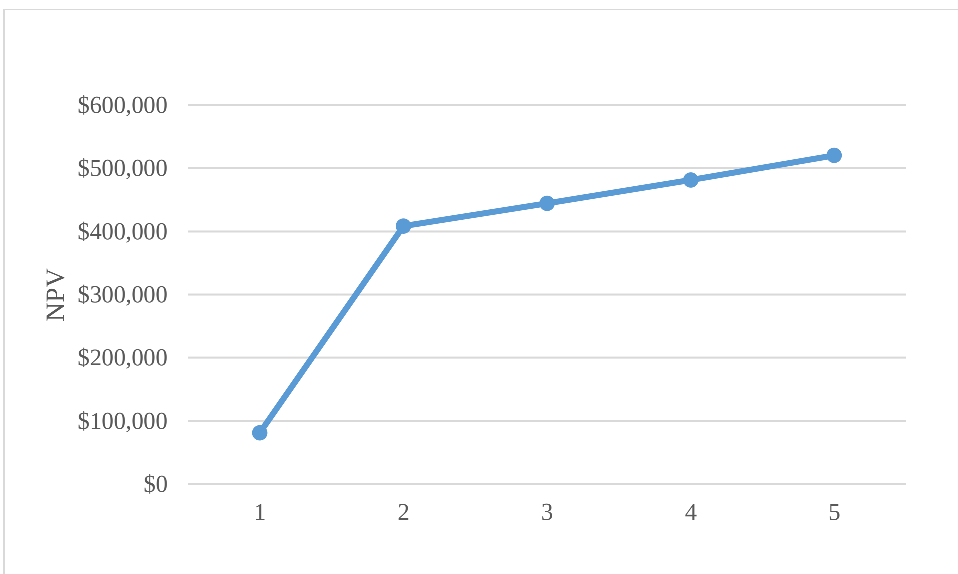


Figure 4.27 NPV results of combined EEM and EFM

The NPV results displayed Figure 4.27 imply that the combined EEM+EFM investment at budget 5 has the maximum investment payback over twenty years. The optimal EEM and EFM package brings the peak demand down below 200 kW. Although TOU-GS-2 option A has a higher energy rate, the result of the optimization analysis suggests that the financial benefit of reduced demand charges exceeds the rise in the energy price.

4.1.6 Case 5: Southern California Edison TOU-GS-3 Option B

This case adopts the Southern California Edison's schedule TOU-GS-3 option B rates to calculate the cost of electricity and to evaluate the best measures and investment strategy to reduce demand charges. The case building's peak demand is 257.87 kW. If the end user successfully attempts to reduce the peak demand below 200 kW, they could switch to schedule TOU-GS-2 option B, which has a higher energy rate, but a lower demand charge.

The first step is to calculate the monthly electricity bill. The customer will be billed for facility-related demand and time-related demand, which includes on-peak and partial-peak demand. Table 4.13 details the steps to calculate the monthly electricity bill in August. The total amount to be paid by the building in August is $18,294.47.

Table 4.14 Calculation of the monthly electricity bill

Customer Charge		1 month	@	$466.13	$466.13
	Facility	257.87 kW	@	$17.81	$4,592.66
	On-Peak	257.87 kW	@	$17.42	$4,592.66
	Partial-Peak	239.09 kW	@	$3.43	$820.08
Total Demand Charges					$10,005.40
Subtotal					$10,471.53
	On-Peak	30,314.67 kWh	@	$0.12	$3,497.40
	Partial-Peak	26,814.37 kWh	@	$0.08	$2,095.01
	Off-Peak	17,390.51 kWh	@	$0.06	$1,033.69
Total Energy Charges		77,519.15 kWh			$6,626.10
Subtotal					$17,097.63
Sales Tax		$17,097.63	@	7%	$1,196.83
Total Electric Charges					$18,294.47

It is worth mentioning that case 4 and 5 both apply to SCE's customers with peak demand greater than 200 kW but less than 500 kW. The customer can choose which option they want to enroll in. SCE TOU-GS-3 option A has a higher energy rate, but a lower demand charge. Buildings with high energy consumption and a relatively low peak demand should choose option B to save on energy bills. By comparing the monthly electricity charge in case 4 and 5, we could draw the conclusion that for our reference office building, before applying any EFM or EEM, choosing the TOU-GS-3 option B with time-related demand and DR incentive has the lower electricity bill.

The next step is to determine the optimal investment in EFMs for the 5 distinct budgets. Figure 4.28, Figure 4.29 and Figure 4.30 show demand charge savings and investments of implementing the optimal EEMs, EFMs, and combined measures. The result from these analyses reveals that the optimal investment strategy for budget 5 achieves the maximum NPV in twenty years.

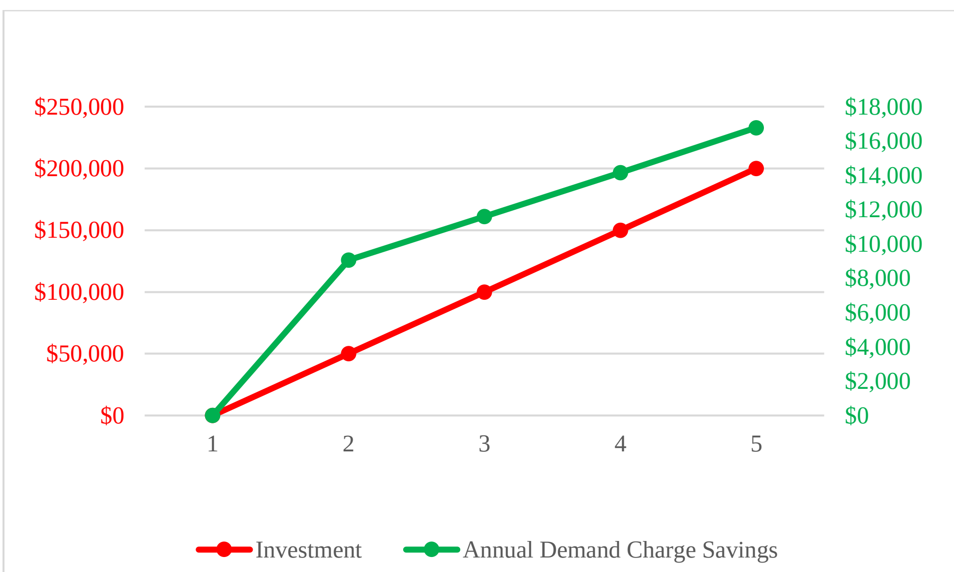


Figure 4.28 Investment and demand charge savings of EEMs

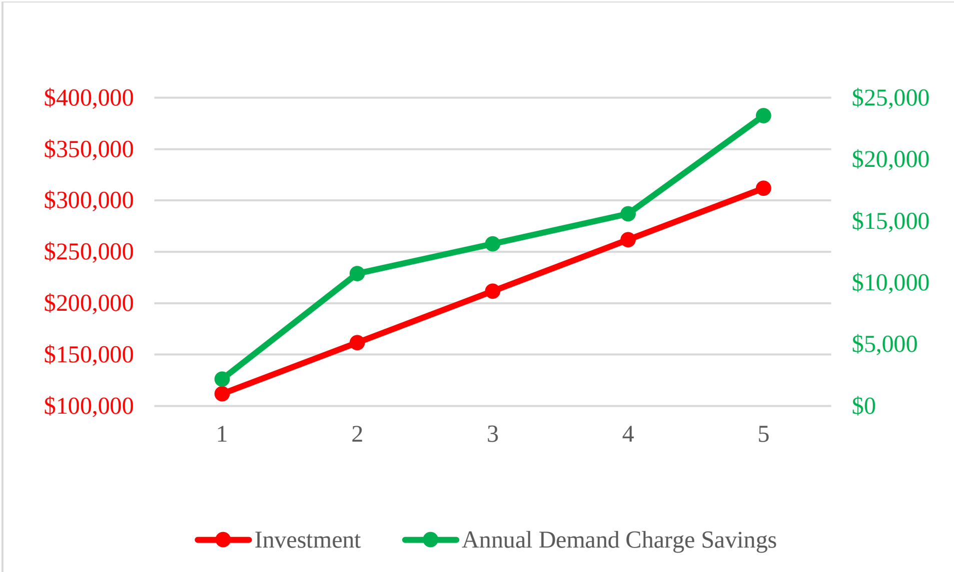


Figure 4.29 Investment and demand charge savings of EFMs

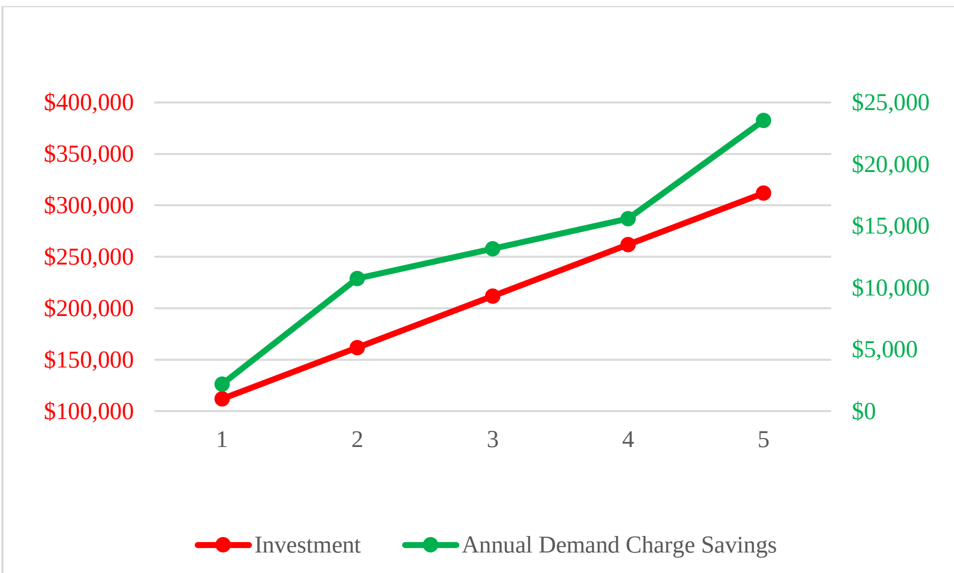


Figure 4.30 Investment and demand charge savings of combined EEM+EFM

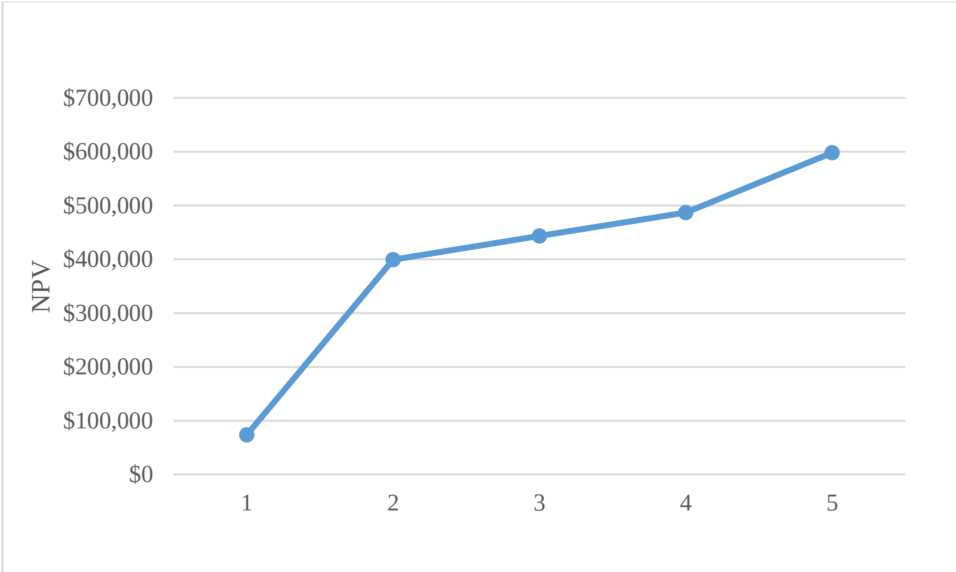


Figure 4.31 NPV results of combined EEM and EFM

The NPV results displayed Figure 4.27Figure 4.31 imply that the optimal investment strategy at budget 5 has the maximum investment payback over twenty years. Case 4 and 5 are different options of the same electricity rate that customers can choose from. In both cases, the optimization result suggests that the peak demand can reduce below 200 kW, which indicates that the financial benefit of reduced demand charges exceeds the rise in the energy price. By comparing the result of case 4 and 5, we can conclude that for the reference office building, option B of TOU-GS-3 and TOU-GS-2 has a lower monthly utility bill and a higher NPV in twenty years compared to option A.

4.2 Reference Hospital Building

The reference hospital building is located in Atlanta, GA. The total area of the six-story building is 3000 m^2. The setpoint temperature of the building is 21.1℃ for heating and 22.2℃ for cooling. The primary energy source for heating and domestic hot water is natural gas, and the primary energy source for cooling is electricity. The maximum cooling capacity of the chiller is

320 kW. Table 4.15 lists the simulated monthly peak demand and consumption. The summer peak load is 302 kW occurring in August. Figure 4.32 illustrates the categorical distribution of annual energy in the hospital building. Cooling and appliance are the top two energy consumers respectively.

Table 4.15 Monthly peak demand and energy consumption

	Peak Demand (kW)	Monthly Total Power (kWh)
Jan	227	75034
Feb	255	76419
Mar	273	103217
Apr	277	106130
May	286	120521
Jun	284	121452
Jul	302	126726
Aug	304	132146
Sep	298	114249
Oct	279	102153
Nov	242	89424
Dec	230	79429

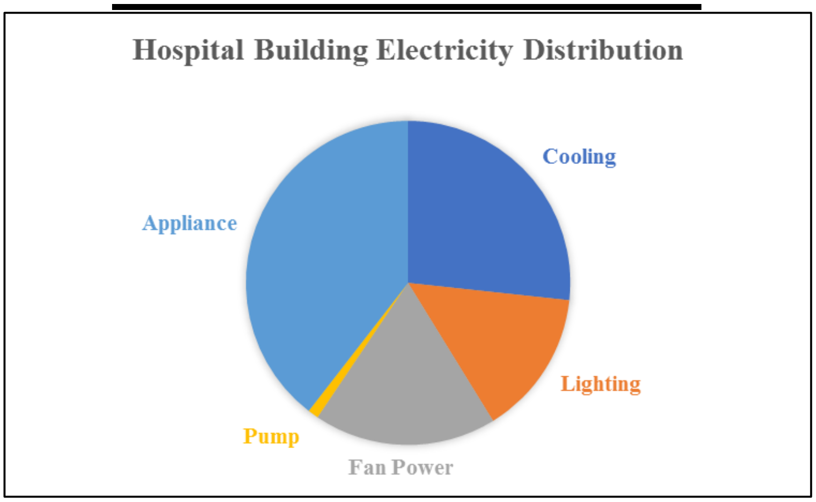


Figure 4.32 Categorical distribution of electricity usage in the hospital building

Healthcare buildings generally have high energy demand (Renedo et al. 2006 and Vanhoudta 2011). Hospitals have a large fluctuation in the hourly and daily loads mostly due to the heavy plug load from medical devices and heavy duty building systems. If the facility manager could make the load in hospital buildings more flexible, the effects on the monthly bill are expected to be larger than in the office building case.

Hospitals are generally large facilities offering around-the-clock operation and significant load shedding potential, which makes them good candidates for DR programs. On hot summer afternoons, hospital cooling loads and lighting systems will be operating at full capacity and will coincide with utility peaks. As a result, a hospital will typically be able to reduce 10 to 15 percent of loads by shifting noncritical loads, such as the cafeteria and lounge lighting, to off-peak hours.

4.2.1 Sensitivity Analysis

A first order SA is conducted to identify the factor that has the most significant impact on peak demand and total energy consumption of the building in this subsection. The dependency of the peak demand on the chosen variables can best be shown through the resulting distribution of outcomes as a function of the possible variation of input variables.Table 4.16 lists the building parameters, which are assumed to have a value randomly selected from a uniform distribution between a min and max value as given in the table. In energy efficiency and renewable energy interventions, optimal parameters remain the same as in the office building case. However, in energy flexibility intervention, a new optimization variable, load shifting through schedule adjustment, is added to the optimization pool.

Table 4.16 List of optimal variables

	Building Parameters	Value		Cost
		Min	Max	
Energy Efficiency Intervention	Infiltration Rate($m^3/h/m^2$)	0.2	0.8	\$4-\$10/m
	Wall Insulation Thickness (mm)	0	100	\$10-\$17/m^2
	Emissivity of Roof	0.4	0.9	\$10-\$22/m^2
	Solar Reduction Factor	0.8	1	\$45-\$65/each window
	Window SHGC	0.25	0.8	\$450-\$650/each window
Energy Flexibility Intervention	Temperature Control	0	2.5	Productivity lost
	Lighting Dimmer	0	30	\$300/each dimmer
	Voltage Throttling	0	1	Productivity lost
	Schedule Adjustment	0	1	\$0
Renewable Energy	Area of the PV System (m^2)	0	200	\$520 per m^2

There are two types of loads in a typical hospital, critical load and administrative load. The critical load includes patient, emergency, and operating room's load. The administrative load includes cafeteria, office, physical therapy, nurse station load. Load shifting by changing the daily operational policy and time of high power-consuming equipment can shift building loads to times when electricity prices are lower and to reduce loads. For simplicity, we introduce the schedule adjustment as a binary parameter in our analysis. The building operator determines whether or not to implement this measure. In chosen hospital building, the load shifting is realized by implementing a 50% of administrative appliance load shifting from 12 p.m. to 6 p.m. to 3 p.m. to 9 p.m. Figure 4.33 shows the appliance schedule before and after the adjustment. The cost of load shifting is related to the organizational change that needs to be implemented. These costs could be determined through an organizational cost analysis, related to staffing parameters and schedules, longer opening hours of certain (outpatient) departments, etc. This thesis only looks at the economic saving potential of load shifting in hospital buildings. Therefore, it is assumed that there is no cost of the load shifting in the optimization process.

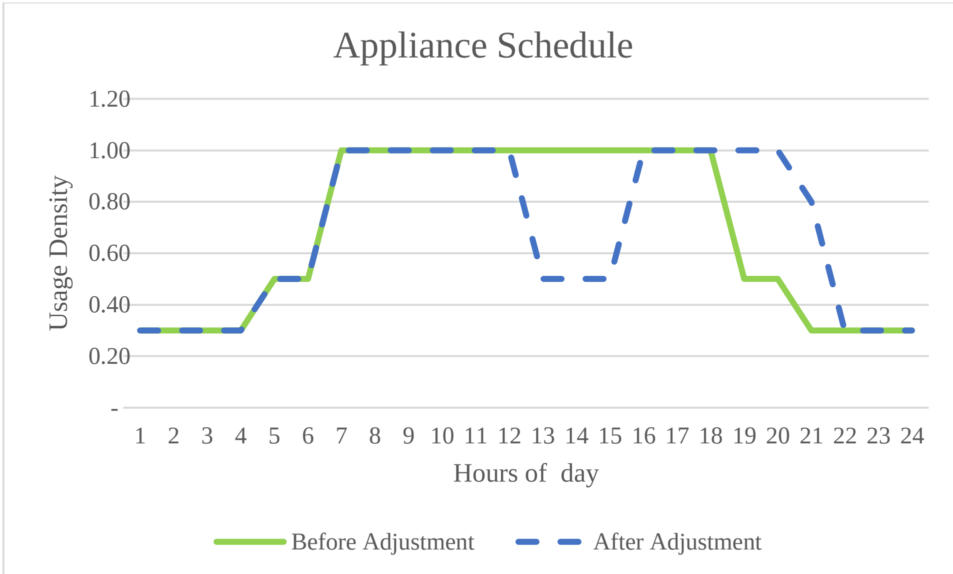


Figure 4.33 Appliance schedule before and after the load-shift adjustment

In the first step, the SA of the billing demand of the building is conducted. Figure 4.34 shows the distribution of the peak demand as the result of varying the EEM/EFM parameters based on the choice of measures, which illustrates that the billing demand cannot reduce to 200 kW with the proposed measures.

Figure 4.35 and Figure 4.36 rank the significance of each parameter in the resulting peak load distribution based on the change in output mean and regression coefficient. In a tornado diagram, the top four bars represent variables that contribute the most to the variability of the outcome and therefore on what the building owner should focus. The top four factors that have the most significant impact on the billing demand are found to be: the SHGC of the window, the schedule adjustment, the solar reduction factor, and the temperature control. Schedule adjustment ranks among the most influential parameters because it shifts major electricity load from noon hours to evening hours. Give the fact that peak demand usually occurs during hot summer noon hours, shifting the load to partial-peak or off-peak hours can have the highest impact on peak demand reduction.

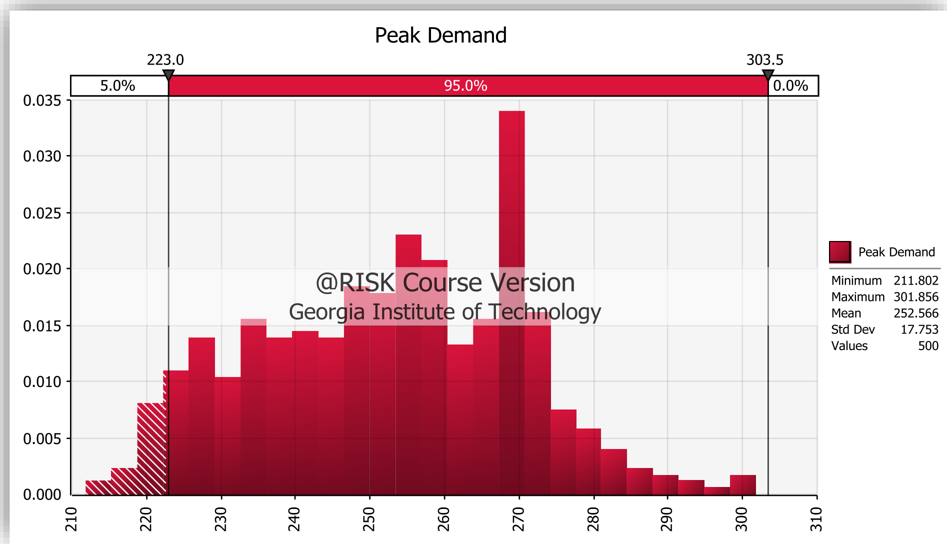


Figure 4.34 Distribution of the peak demand

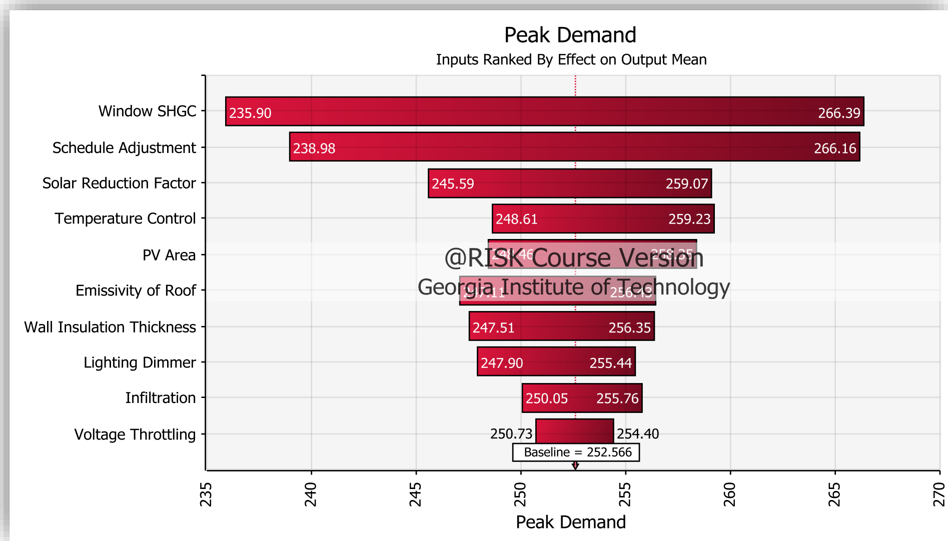


Figure 4.35 SA ranking based on the change in output mean

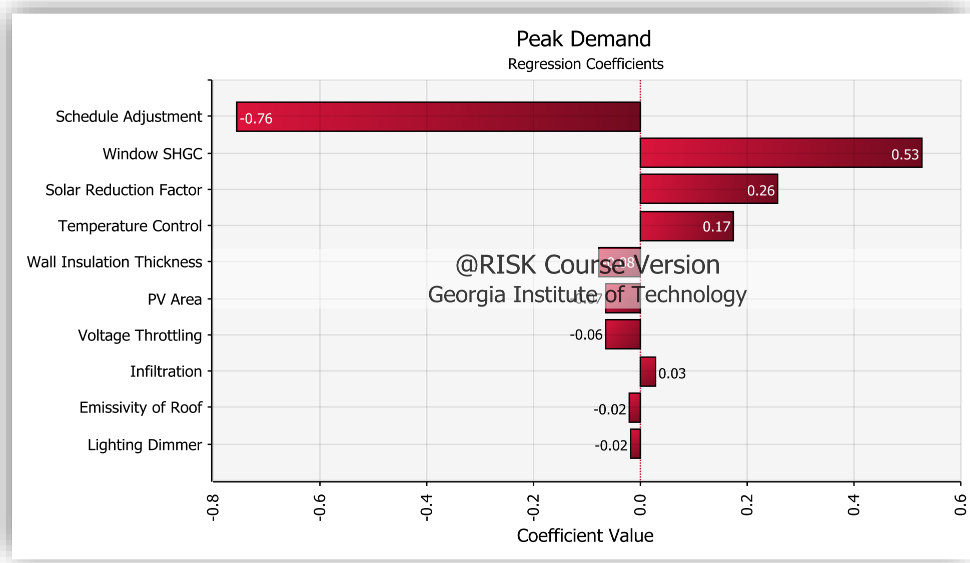


Figure 4.36 SA ranking based on regression coefficient

The second step of the SA is carried out on the coincident peak demand of the building. Figure 4.37 illustrates the distribution of the coincident peak demand as the result of varying EEM/EFM parameters, which implies that the coincident peak demand in the building can be reduced to 140 kW with the proposed optimization factors. Figure 4.38 and Figure 4.39 rank the significance of each parameter in the resulting coincident peak load distribution based on the change in the output mean and the regression coefficient. The top three factors that have the most significant impact on the coincident peak demand are the schedule adjustment, temperature control, and the window SHGC. Schedule adjustment ranks among the most influential parameters because it shifts major electricity load from peak hours to partial-peak or off-peak hours, which significantly reduce the coincident peak demand. The temperature control ranks as the second most significant factor. Increase the temperature control actually cause a sudden rise in the peak demand. This is due to the fact that the room temperature keeps rising above the regulated setpoint after the adjustment, which calls the chiller to come back on, most likely operating at its maximum capacity.

To avoid this, the voltage throttling methods are introduced to "manipulate" the capacity of the chiller, in which case the chiller will act temporarily as a smaller system than its actual capacity thus reducing the peak load over the full period.

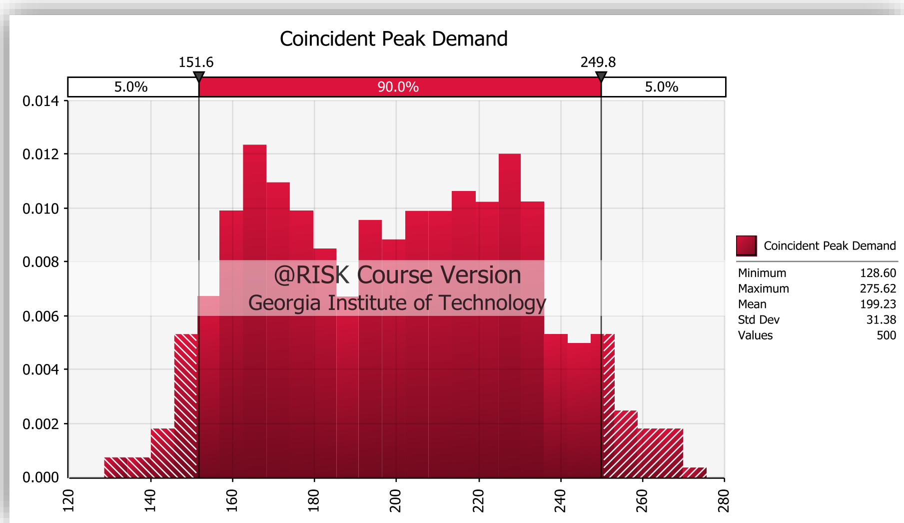


Figure 4.37 Distribution of the coincident peak demand

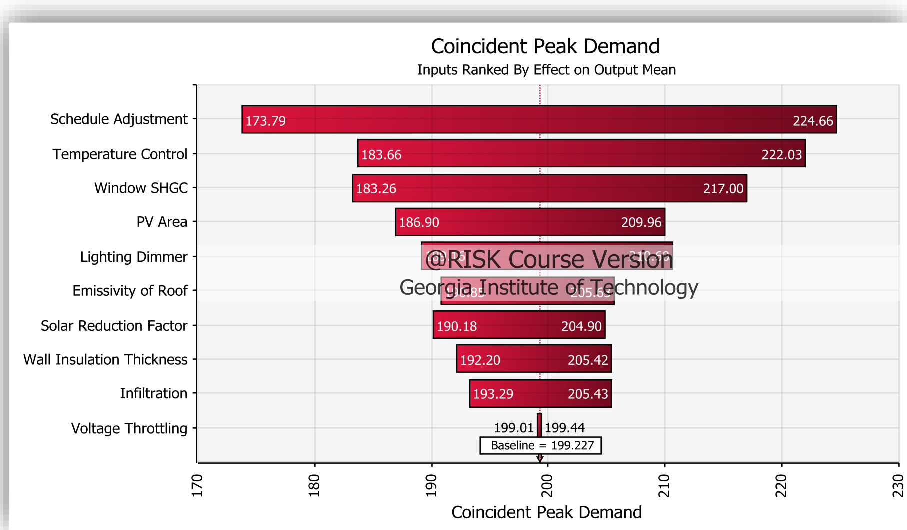


Figure 4.38 SA ranking based on the change in output mean

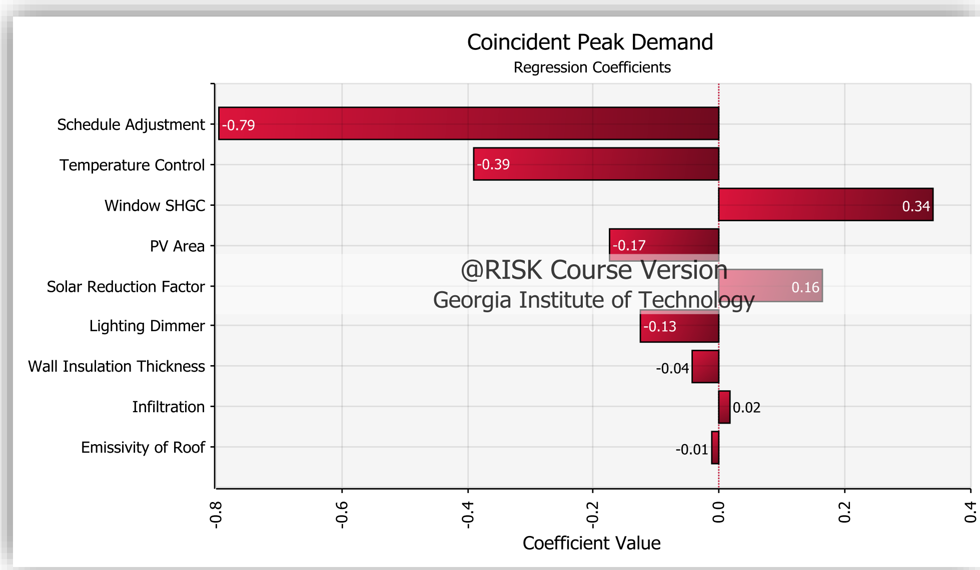


Figure 4.39 SA ranking based on regression coefficient

The last step of the SA is implemented on the total energy consumption of the building. Figure 4.40 shows the distribution of the total energy consumption as the result of varying the EEM/EFM parameters. Figure 4.41 and Figure 4.42 rank the role of each parameter in the resulting total energy consumption distribution based on the change in output mean and regression coefficient. The top three factors that have the most significant impact on the total energy consumption are window SHGC, solar reduction factor and PV area. Schedule adjustment that ranks the most significant factor in the SA study of peak demand and coincident peak demand does not show a significant impact on the total energy consumption. This is because temporarily adjust the operational schedule is merely a load shifting strategy that does not impact the total energy consumption.

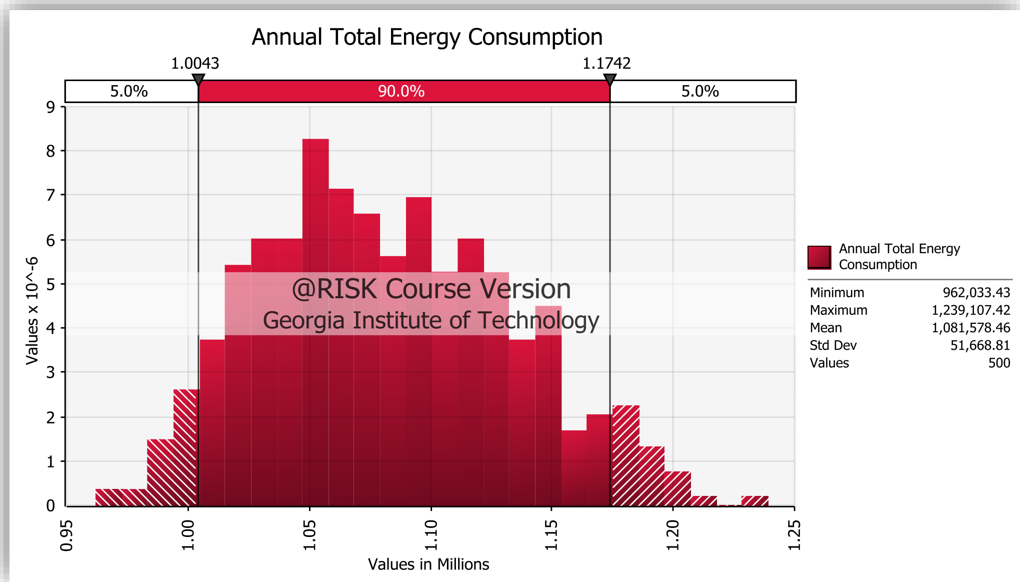


Figure 4.40 Distribution of the total energy consumption

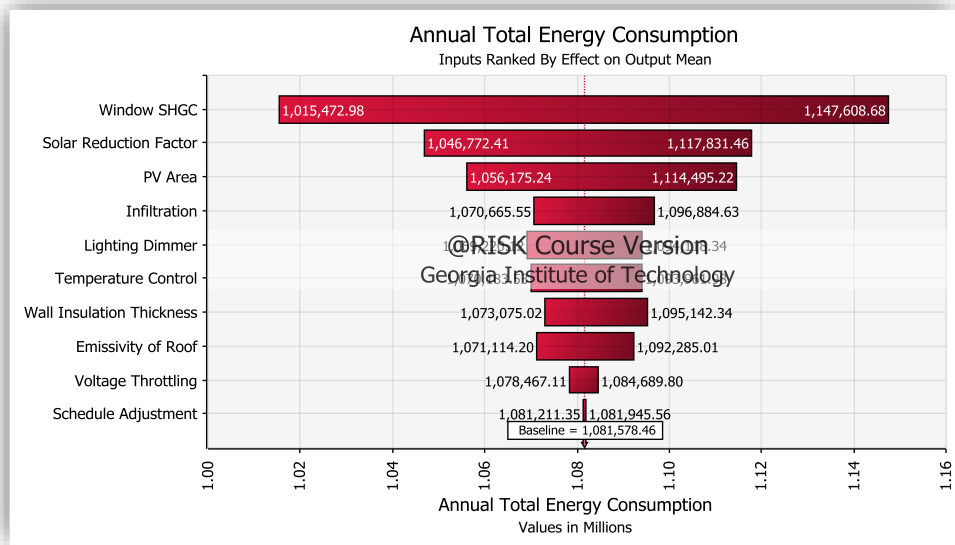


Figure 4.41 SA ranking based on the change in output mean

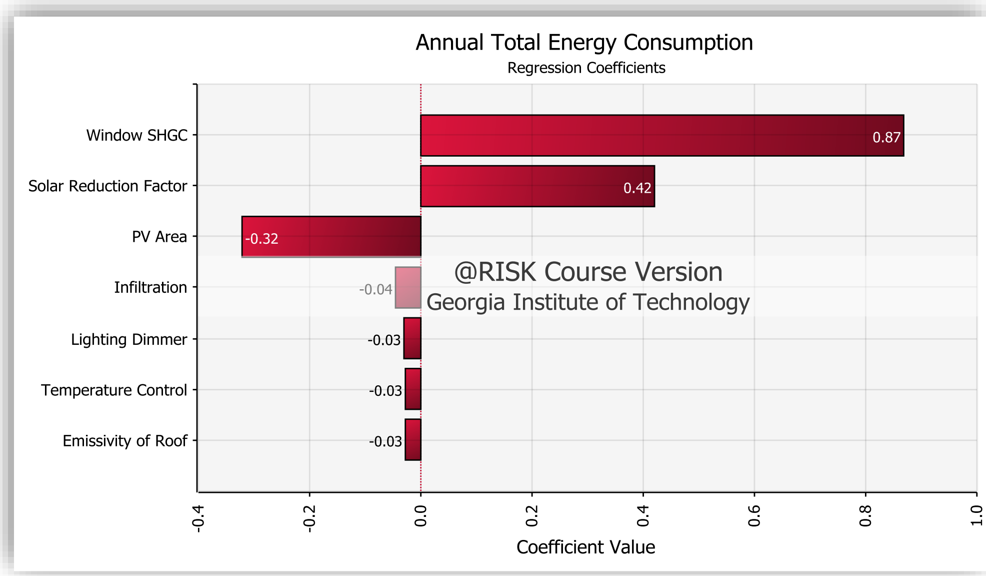


Figure 4.42 SA ranking based on regression coefficient

4.2.2 Case 1: Georgia Power PLM-11

This case adopts the GP's schedule PLM-11 to calculate the cost of electricity and to evaluate the optimal combination of EFMs to reduce demand charges. The case building's peak demand is 304 kW, which is difficult to reduce below 30 kW. Therefore, for the case building, demand charges are linearly correlated to the peak demand value in each month under the PLM-11.

The first step is to calculate the monthly electricity cost. Taking the summer month August as an example, the first part is to determine the peak demand in the current month. According to Table 4.15, the peak power in the current month is 304 kW. According to PLM-11, this value is higher than the 95% of the highest peak demand in summer months and 60% peak power in winter months, the billing demand power in August is 304 kW. The second part is to calculate the HUD in August.

$$\mathrm{HUD} = 132146(\mathrm{kWh})/304\ (\mathrm{kW}) = 435$$

The HUD in August is higher than 400 hours but less than 600 hours. According to Appendix A, the electricity price is \$0.008606 per kWh. Table 4.17 illustrates the steps to calculate the monthly electricity bill in August. The total amount to be paid by the building is \$9589.48. The result reveals that the total energy charge is only 10% of the total bill, while the demand charge is almost 30% of the total bill.

The next step is to determine the optimal investment in EFMs under the five distinct EEM budgets, the results are shown in Figure 4.43. The red curve represents the investments and the green curve corresponds to annual demand charge savings. Both curves go upward, and budget 2 turns out to have the highest efficiency of investment when only looking at demand charge reduction.

Table 4.17 Calculation of the monthly electricity bill

Customer Charges	1 month	@	\$19.00	\$19.00
Demand Charges	304 kW	@	\$8.24	\$2,504.96
Energy Charges	132146 kWh	@	\$0.008	\$1,510.43
Subtotal				\$4,034.39
ECCR Charges	\$4,034.39	@	0.100131	\$403.97
NCCR Charges	\$4,034.39	@	0.075821	\$305.89
FCR Charges	132146 kWh	@	\$0.03	\$3,964.38
Subtotal				\$8,708.63
MFF Charges	\$8,708.63	@	0.029109	\$253.50
Subtotal				\$8,962.13
Sales Tax	\$8,962.13	@	7%	\$627.35
Total Electric Charges				**\$9,589.48**

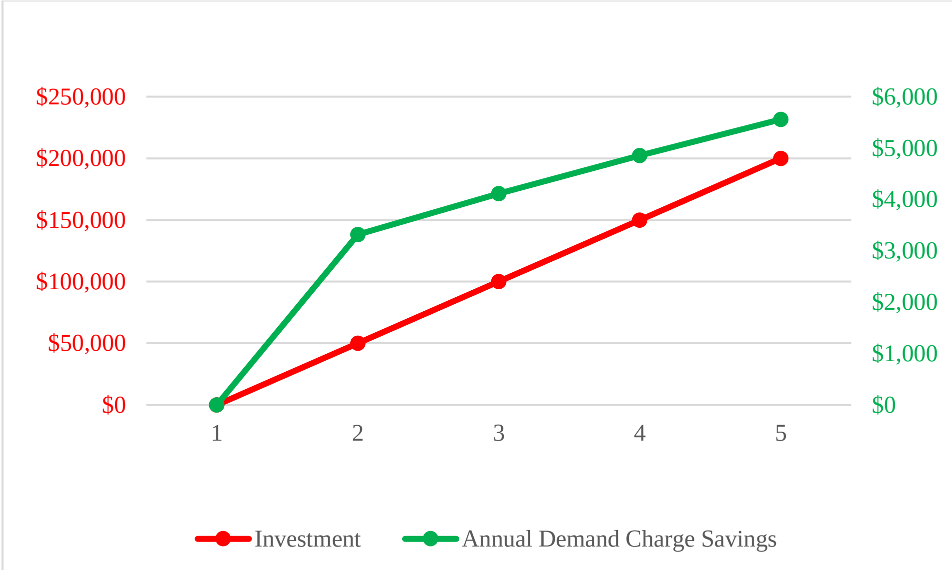


Figure 4.43 Investment and demand charge savings of EEMs

Figure 4.44 shows demand charge savings and investments of implementing the optimal EFMs at each EEM budget level. The red curve represents the investments, which are the highest for budget 3. At budgets 2, 4 and 5 the chosen EFM set is very similar and has the same investments, which are lower than those for budget 3. The green curve corresponds to demand charge savings, which shows a downward trend from budget 1 to 5, except a slight increment for budget 3. The declining trend of demand charge saving curve is caused by the fact that the potential of demand charge savings by EFMs is impacted by the energy efficiency of the building. As more budget is allocated to enhance energy efficiency features, the space for demand charge reduction through improving energy flexibility in buildings is compressed. Figure 4.45 illustrates the total investment and demand charge savings for each budget level. The result reveals that budget 2 has the maximum efficiency of investment in interventions when only looking at demand charge savings.

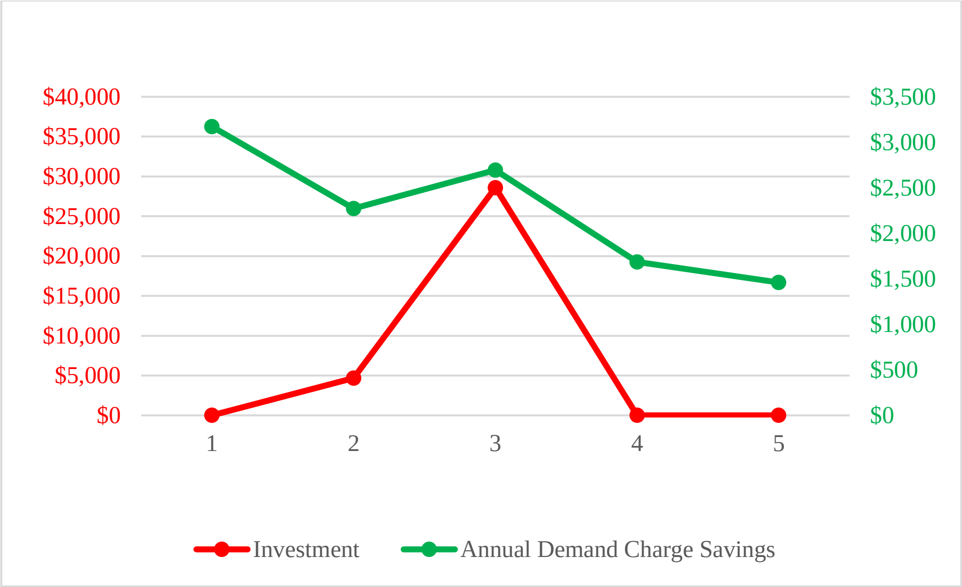


Figure 4.44 Investment and demand charge savings of EFMs

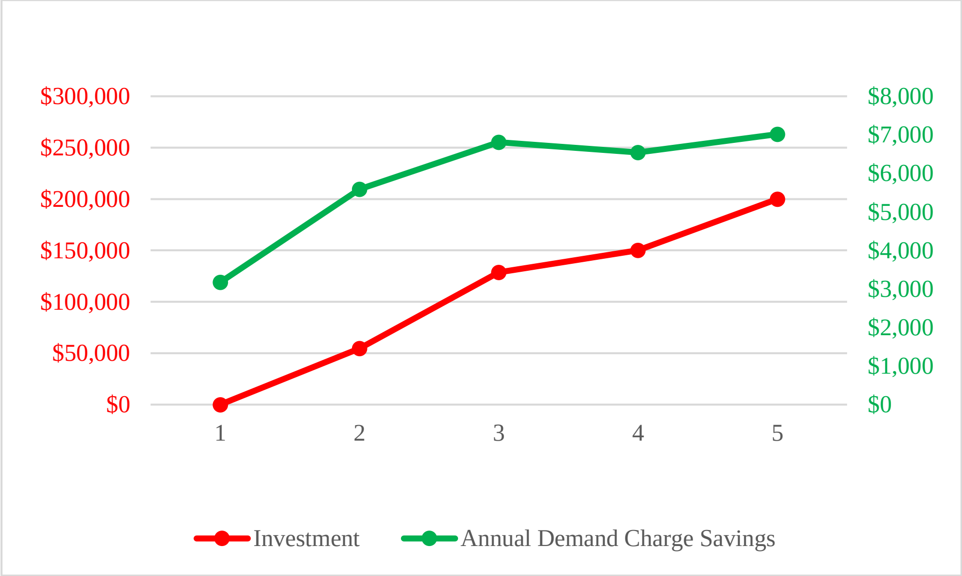


Figure 4.45 Investment and demand charge savings of combined EEM+EFM

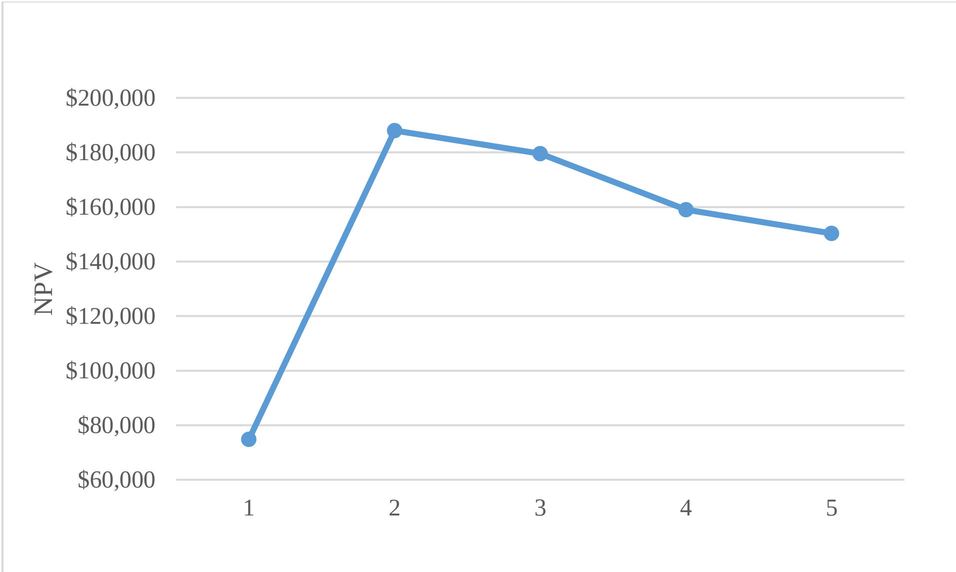


Figure 4.46 NPV results of combined EEM and EFM

The NPV results displayed in Figure 4.46 imply that the optimal investment for budget 2 has the maximum investment payback over twenty years. Increase the investment in EEMs and EFMs may lead to a decrease in the total NPV.

4.2.3 Case 2: Pacific Gas & Electricity A-10 Non-TOU

This case adopts the PG&E's schedule A-10 non-TOU rates to calculate the cost of electricity and to evaluate the best measure and investment strategy to reduce demand charges.

The first step is to calculate the monthly electricity bill. Taking the summer month August as an example, the first part is to decide the peak demand in the current month. The customer will be billed for demand according to the customer's maximum demand, which equals to the highest 15-minute average in the month. According to Table 4.6, the billing demand in August is 304 kW. Appendix B lists the rate structure of schedule A-10 non-TOU rate. Table 4.18 details the steps to calculate the monthly electricity bill in August. The total amount to be paid by the building in August is $29,540.67. The result reveals that the demand charge is 20% of the total bill.

Table 4.18 Calculation of the monthly electricity bill

Customer Charge	31 days	@	$4.60	$142.59
Demand Charges	304 kW	@	$16.78	$5,101.12
Energy Charges	132146 kWh	@	$0.14	$18,500.44
Transmission Rate Adjustments	132146 kWh	@	$0.00	$623.73
Public Purpose Programs	132146 kWh	@	$0.01	$1,871.19
Nuclear Decommissioning	132146 kWh	@	$0.00	$196.90
Competition Transition Charges	132146 kWh	@	$0.00	$132.15
DWR Bond	132146 kWh	@	$0.01	$725.48
New System Generation Charge	132146 kWh	@	$0.00	$314.51
Subtotal				$27,608.10
Sales Tax	$27,608.10	@	7%	$1,932.57
Total Electric Charges				$29,540.67

The next step is to determine the optimal investment in EFMs under five different EEM budget levels. Figure 4.47 displays demand charge savings and investments of implementing optimal EEMs at each budget level. The red curve represents the investments, and the green line corresponds to demand charge savings. Both curves go upward. Among five budget levels, level 2 turns out to have the highest efficiency of investment when only considering demand charges.

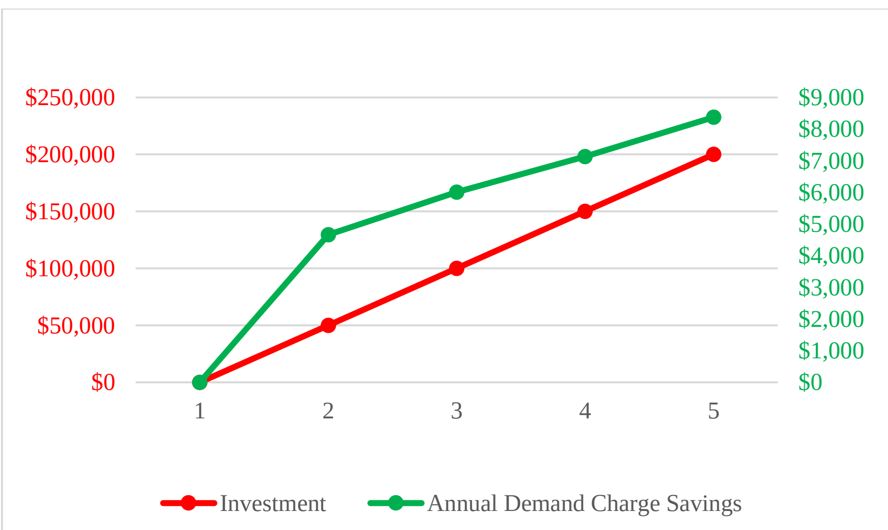


Figure 4.47 Investment and demand charge savings of EEMs

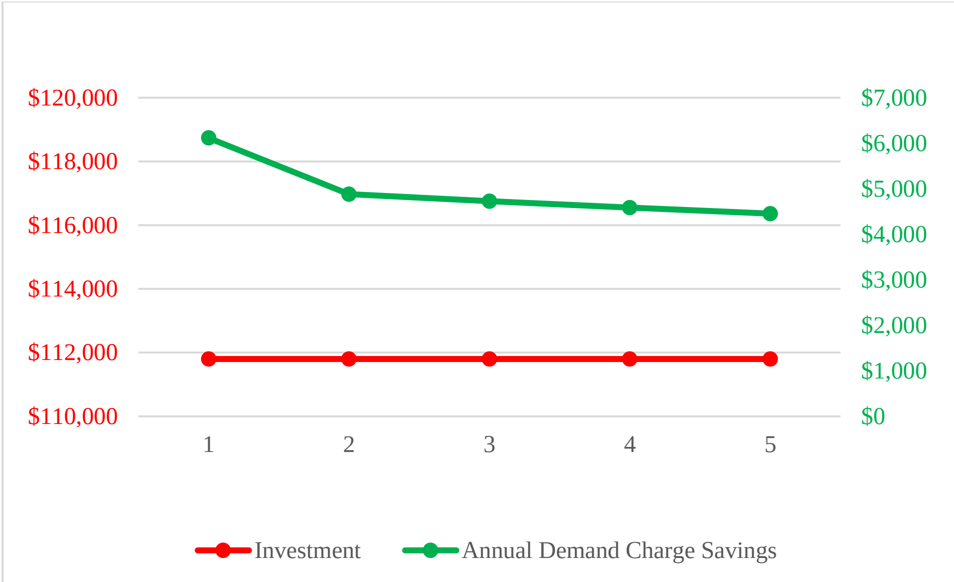


Figure 4.48 Investment and demand charge savings of EFMs

Figure 4.48 shows demand charge savings and investments of implementing the optimal EFMs. Investments are identical at each EEM budget level. The curve of annual demand charge savings declines from budget 1 to 5, because the increased budget on EEMs compresses the space of financial savings through EFMs. In the office building case 2, there is a steep rise at budget 5, because executing EFMs at the high EEM budget level successfully brings the peak demand down below 200 kW, at which point no demand charge will be applied to the building. However, the hospital building has a higher peak demand, the proposed EEMs and EFMs cannot reduce the peak demand below 200 kW even at the maximum budget. Therefore, budget 1 has the maximum demand savings from EFM investment.

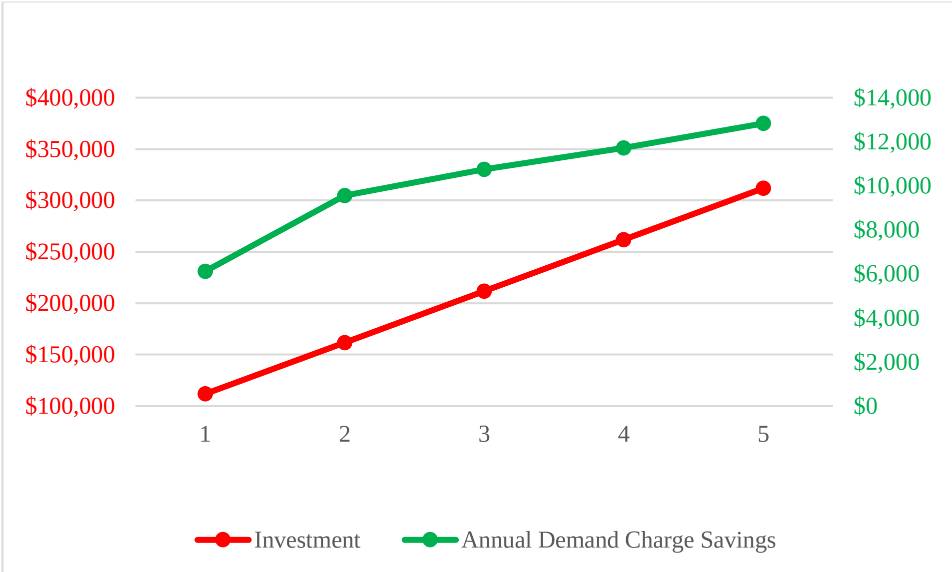


Figure 4.49 Investment and demand charge savings of combined EEM+EFM

Figure 4.49 depicts the change of total investment and demand charge savings. Both curves go upward. Budget 2 turns out to have the highest efficiency of investment for demand charge reduction.

The NPV result displayed in Figure 4.50 imply that the optimal investment strategy at budget 5 has the maximum investment payback over twenty years. Although the peak demand cannot reduce below 200 kW for this hospital building, the optimization result still suggests that maximizing the investment in EEMs and EFMs achieves the highest NPV. It should obviously be kept in mind that the cost function of the schedule change has been set to zero, which benefits (and inflates) the NPV.

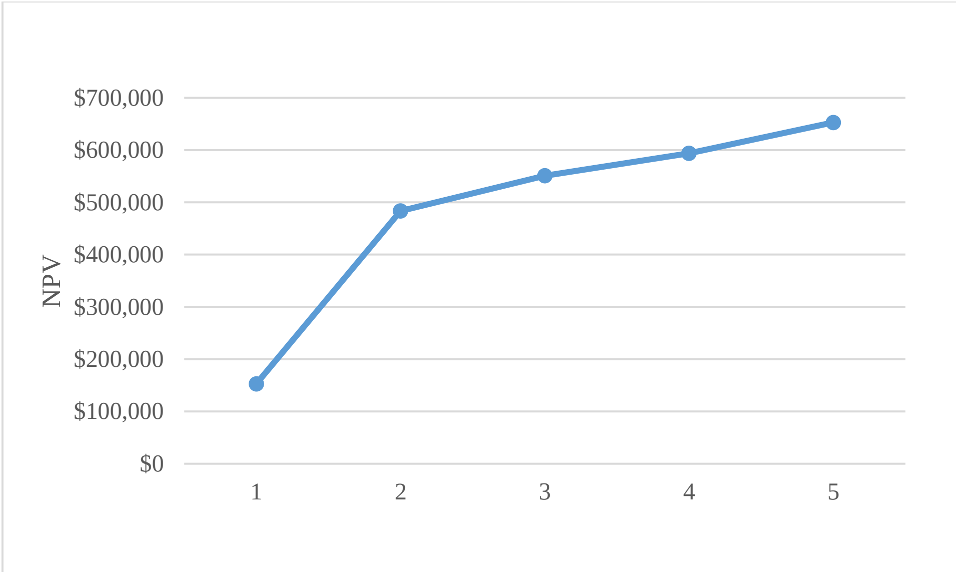


Figure 4.50 NPV results of combined EEM and EFM

4.2.4 Case 3: Pacific Gas & Electricity A-10 TOU

This case employs the PG&E's schedule A-10 TOU rates to calculate the cost of electricity and to evaluate the best measure and investment strategies to reduce demand charges. Different from the flat daily rate structure in case 2, the schedule A-10 TOU adopts a TOU rate structure. Table 2.1 and Table 4.3 details how times of the day are defined and how much is the hourly rate during a day. This rate schedule also includes the PDP rate. In a PDP event day, the customer will be charged $0.9 per kWh from 12 p.m. to 4 p.m. In contrast, they will receive a credit of $3.26 per kW reduction on peak demand in the month that contains the PDP event. Section 4.1 has introduced how to decide the PDP event day. This case adopts the same method. Table 4.19 lists the selection criteria and the date of days that meet the criteria.

Table 4.19 Number of days meets the criteria

T>35.9 ℃	July 8
T>34.9 ℃	July 7, 14, August 1, 2, 18
T>33.9 ℃	June 6, 13, July 6, 9, 13, 21

Table 4.20 Calculation of the monthly electricity bill

Customer Charge	31 days	@	$4.60	$142.59
Demand Charges	304 kW	@	$16.78	$5,101.12
Subtotal				$5,243.71
On-Peak	34855.51 kWh	@	$0.22	$7,658.45
Partial-Peak	34658.66 kWh	@	$0.16	$5,704.47
Off-Peak	59415.99 kWh	@	$0.14	$8,111.47
PDP Events	3440.84 kWh	@	$0.90	$3,096.76
Total Energy Charges	132146 kWh			$24,571.15
Transmission Rate Adjustments	132146 kWh	@	$0.00472	$623.73
Public Purpose Programs	132146 kWh	@	$0.01416	$1,871.19
Nuclear Decommissioning	132146 kWh	@	$0.00149	$196.90
Competition Transition Charges	132146 kWh	@	$0.00100	$132.15
DWR Bond	132146 kWh	@	$0.00549	$725.48
New System Generation Charge	132146 kWh	@	$0.00238	$314.51
Subtotal				$33,678.81
Sales Tax	$33,678.81	@	7%	$2,357.52
Total Electric Charges				$36,036.32

The first step is to calculate the monthly electricity bill. Taking the summer month August as an example, the first part is to decide the peak demand in the current month. The customer will be billed for demand according to the customer's maximum demand, which equals to the highest 15-minute average in the month. According to Table 4.15, the billing demand in August is 304 kW. Table 4.20 details the steps to calculate the monthly electricity bill in August. The total amount to be paid by the building in August is $36,036.32. It is worth mentioning that the rate structure in case 2 and 3 both apply to PG&E's customers with peak demand greater than 200 kW but less than 499 kW. The customer can choose which rate, TOU or non-TOU, they want to enroll in. TOU rate encourages people to improve energy flexibility by charging a higher rate during peak hours and a much lower rate during off-peak hours compared to the flat rate. Buildings with high energy flexibilities should choose TOU rate structure to save on energy bills. By comparing the monthly electricity charge in case 2 and 3, we find out that for the reference hospital building, before applying any EFM or EEM, choosing the non-TOU rate has a relative low electricity cost.

Figure 4.51 shows demand charge savings and investments at given EEM budget levels. Both cost and saving curves go upward. Among five budget levels, budget 2 turns out to have the highest investment efficiency considering only demand charge savings.

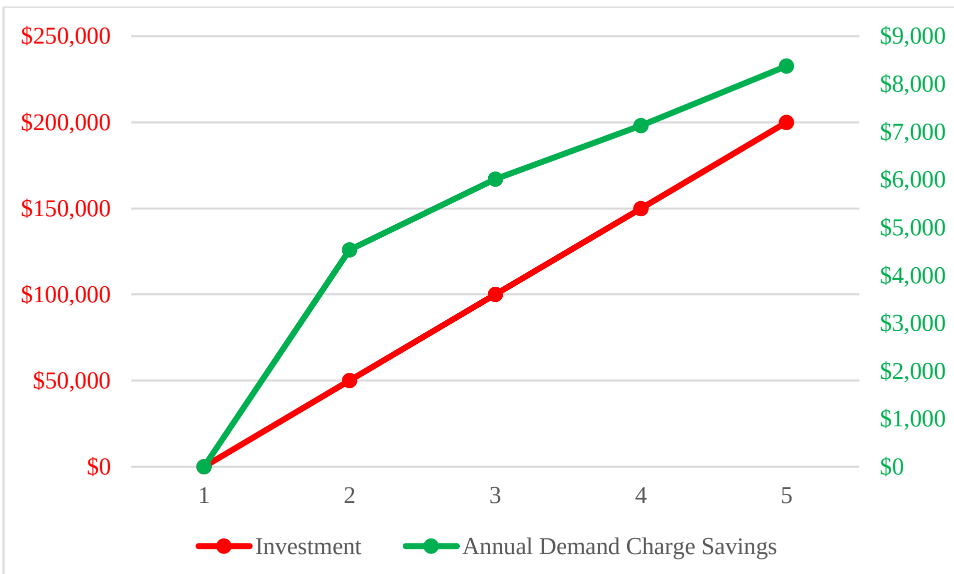


Figure 4.51 Investment and demand charge savings of EEMs

Figure 4.52 details demand charge savings and investments of implementing the optimal EFMs at each budget level. The investment curve remains the same in the five budgets. The demand charge saving from implementing EFMs slowly decline in five budgets, as a result of the increased use of EEMs limiting the saving potential of EFMs.

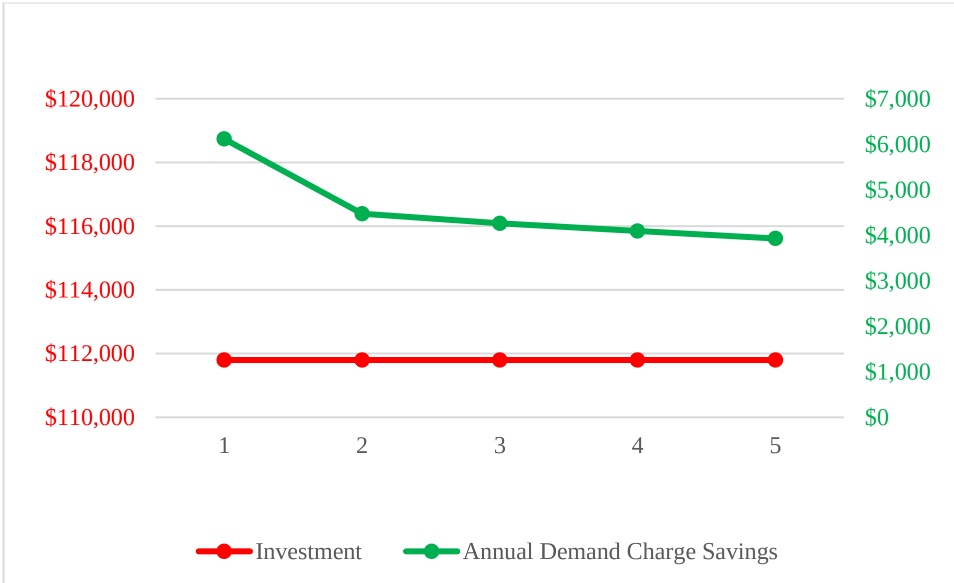


Figure 4.52 Investment and demand charge savings of EFMs

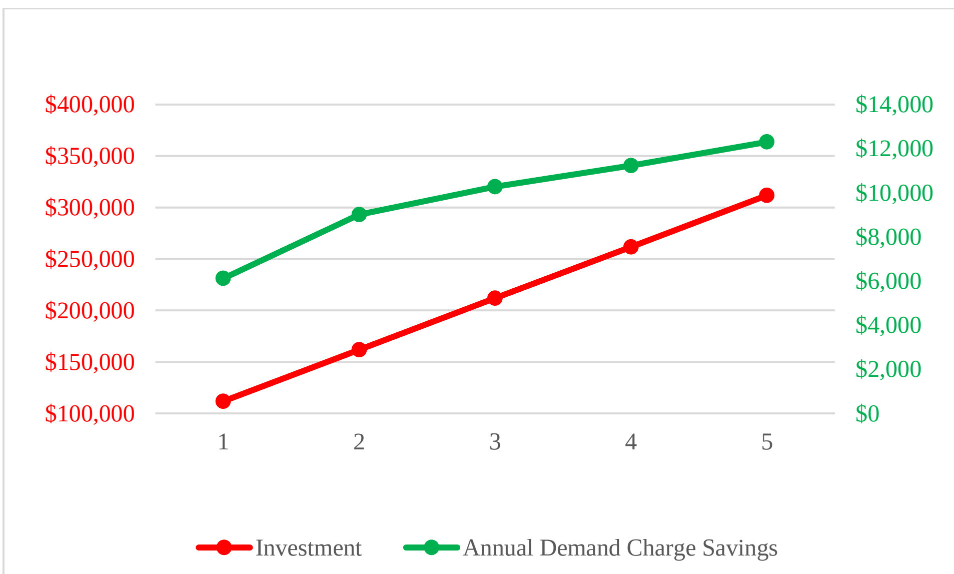


Figure 4.53 Investment and demand charge savings of combined EEM+EFM

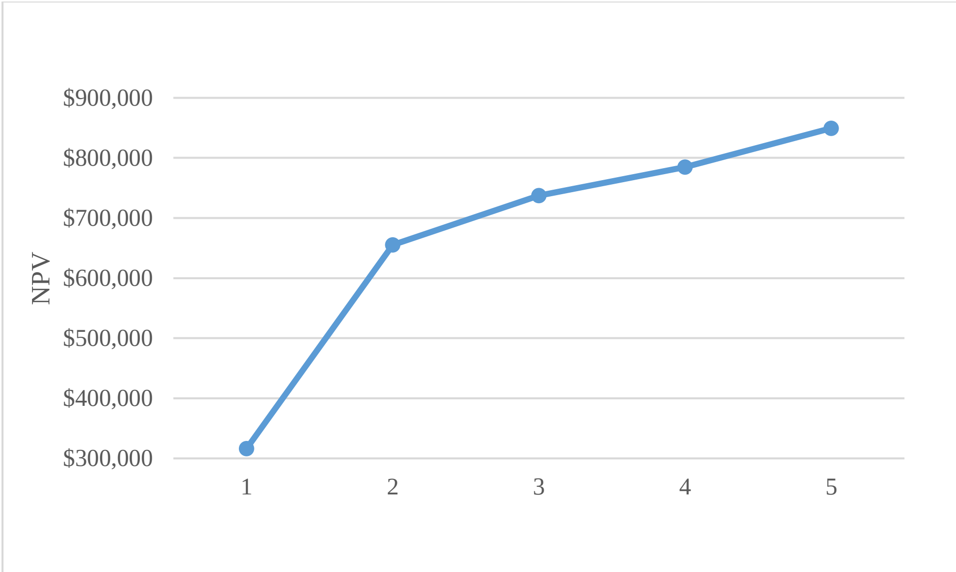


Figure 4.54 NPV results of combined EEM and EFM

Figure 4.53 illustrates the total investment and demand charge savings at each EEM budget level. At budget level 5 we find the highest demand charge savings. The NPV results displayed in Figure 4.54 imply that the optimal investment strategy at budget 5 has the maximum investment payback over twenty years. Case 2 and 3 are different options of the same electricity rate schedule that customers can choose from. Before implementing any EEM or EFM, the non-TOU rate has a lower annual energy rate. But after implementing the optimal strategy suggested at budget 5, the TOU rate can save more and has a higher NPV in twenty years.

4.2.5 Case 4: Southern California Edison TOU-GS-3 Option A

This case adopts the Southern California Edison's schedule TOU-GS-3 option A rates to calculate the cost of electricity and to evaluate the best measures and investment strategy to reduce demand charges.

The first step is to calculate the monthly electricity bill. Taking the summer month August as an example, the first part is to decide the peak demand in the current month. The customer will be billed for demand according to the customer's maximum demand, which equals to the highest 15-minute average in the month. According to Table 4.15, the billing demand in August is 304 kW. Table 4.21 details the steps to calculate the monthly electricity bill in August. The total amount to be paid by the building in August is $27,298.51.

Table 4.21 Calculation of the monthly electricity bill

Customer Charge	1 month	@	$466.13	$466.13
Demand Charges	304 kW	@	$17.81	$5,414.24
Subtotal				$5,880.37
On-Peak	38296.4 kWh	@	$0.32	$12,254.85
Partial-Peak	34658.66 kWh	@	$0.11	$3,812.45
Off-Peak	59415.99 kWh	@	$0.06	$3,564.96
Total Energy Charges	132146 kWh			$19,632.26
Subtotal				$25,512.63
Sales Tax	$25,512.63	@	7%	$1,785.88
Total Electric Charges				$27,298.51

Figure 4.55, Figure 4.56 and Figure 4.57 show demand charge savings and investments of implementing the optimal EEMs, EFMs and both measures together at the five distinct investment levels. The NPV results displayed in Figure 4.58 suggests that the optimal investment strategy at budget 5 has the maximum investment payback over twenty years, which indicates that maximizing the budget for EEM and EFM package will earn the highest financial payback.

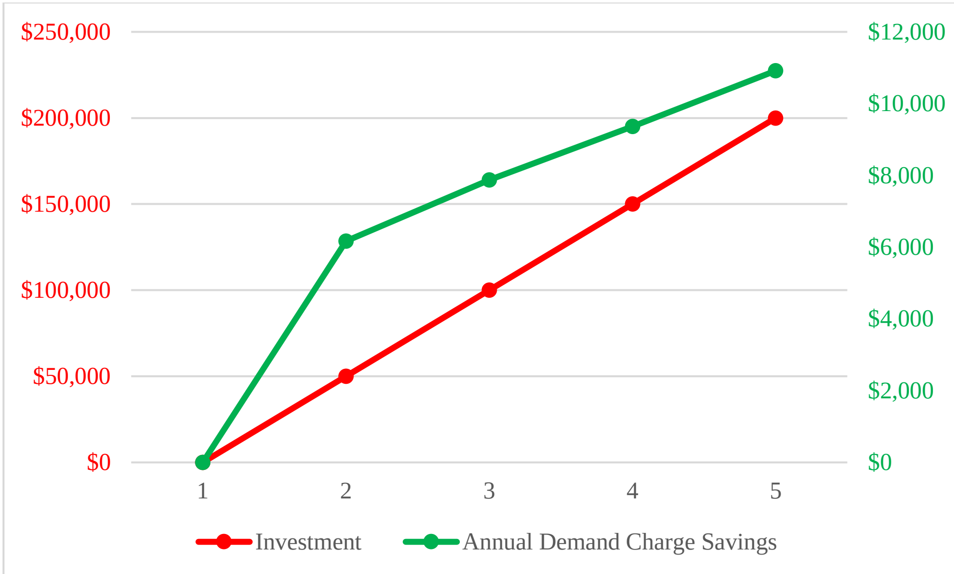


Figure 4.55 Investment and demand charge savings of EEMs

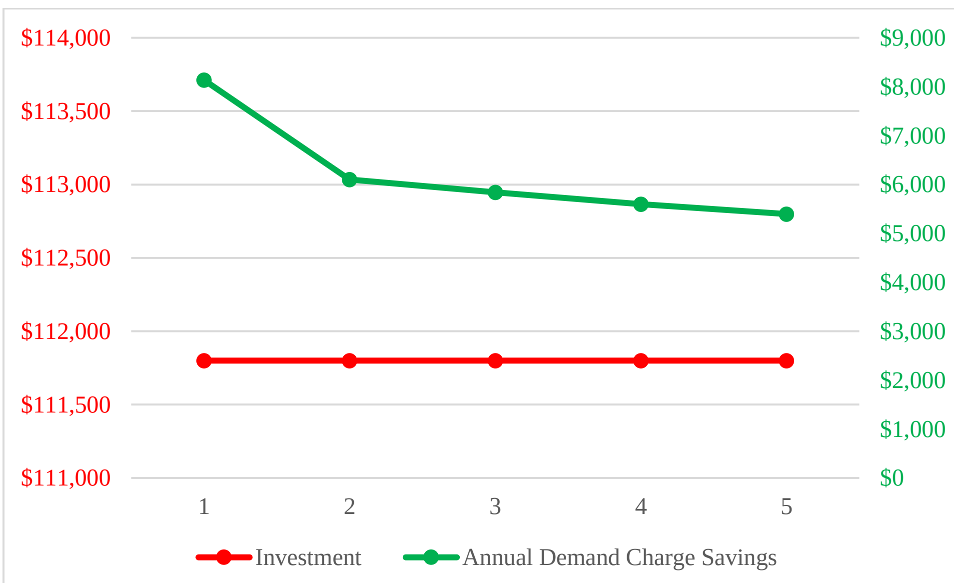


Figure 4.56 Investment and demand charge savings of EFMs

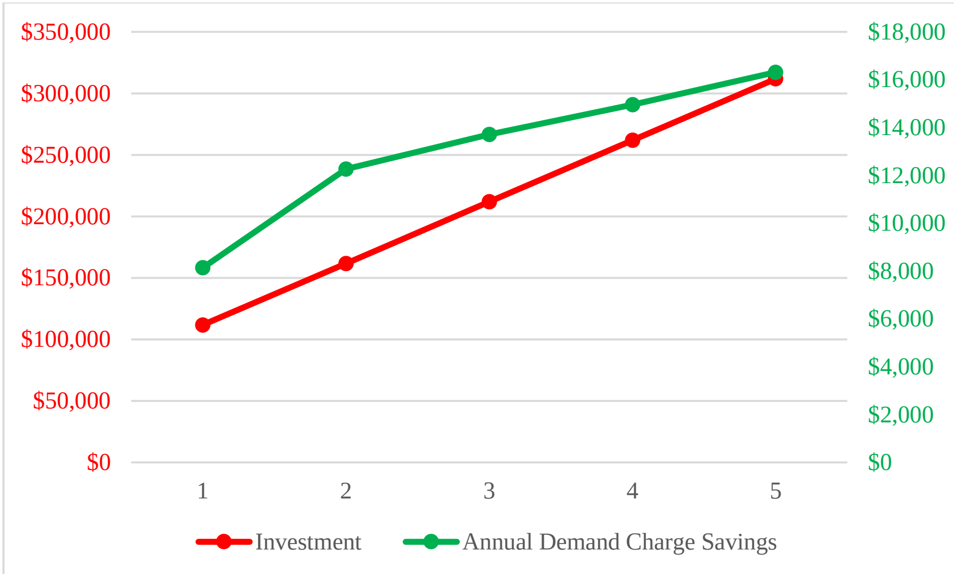


Figure 4.57 Investment and demand charge savings of combined EEM+EFM

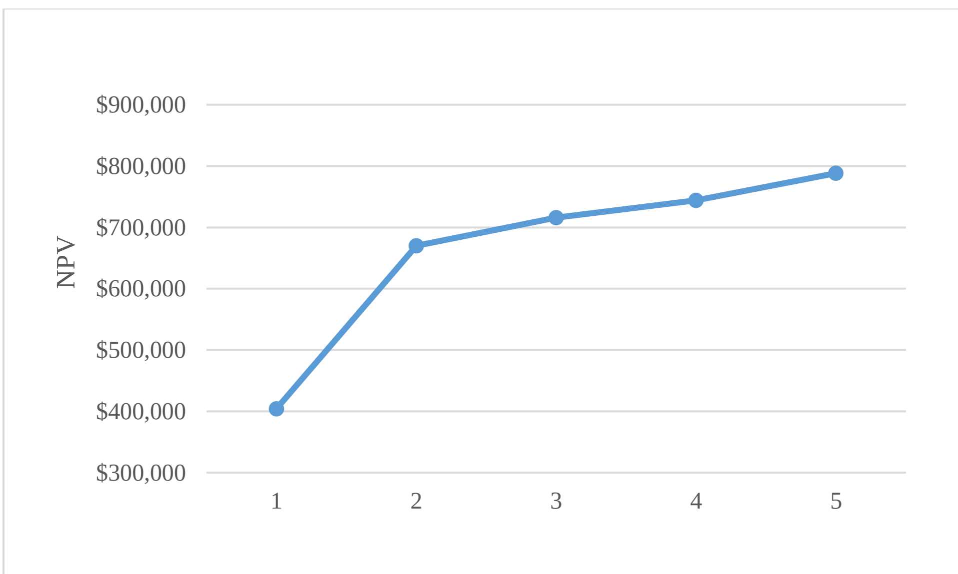


Figure 4.58 NPV results of combined EEM and EFM

4.2.6 Case 5: Southern California Edison TOU-GS-3 Option B

This case adopts the Southern California Edison's schedule TOU-GS-3 option B rates to calculate the cost of electricity and to evaluate the best measures and investment strategy to reduce demand charges.

The first step is to calculate the monthly electricity bill. The customer will be billed for facility related demand and time-related demand, which includes on-peak and partial-peak demand. Table 4.22 details the steps to calculate the monthly electricity bill in August. The total amount to be paid by the building in August is $24,641.42.

Table 4.22 Calculation of the monthly electricity bill

Customer Charge		1 month	@	$466.13	$466.13
	Facility	304 kW	@	$17.81	$5,414.24
	On-Peak	305 kW	@	$17.42	$5,295.68
	Partial-Peak	268.25 kW	@	$3.43	$920.10
Total Demand Charges					$11,630.02
Subtotal					$12,096.15
	On-Peak	38296.4 kWh	@	$0.12	$4,595.57
	Partial-Peak	34658.66 kWh	@	$0.08	$2,772.69
	Off-Peak	59415.99 kWh	@	$0.06	$3,564.96
Total Energy Charges		132146 kWh			$10,933.22
Subtotal					$23,029.37
Sales Tax		$23,029.37	@	7%	$1,612.06
Total Electric Charges					$24,641.42

It is worth mentioning that case 4 and 5 both apply to SCE's customers with peak demand greater than 200 kW but less than 500 kW. The customer can choose which option they want to enroll in. By comparing the monthly electricity charge in case 4 and 5, we could draw the conclusion that for the reference office building, before applying any EFM or EEM, choosing the TOU-GS-3 option B has a lower electricity cost.

Figure 4.59, Figure 4.60 and Figure 4.61 show demand charge savings and investments of implementing the optimal EEMs, EFMs, and combined measures together at the 5 distinct EEM budget levels. The result from these analyses reveals that the optimal investment strategy suggested at budget 2 has the maximum investment efficiency when only considering demand charges.

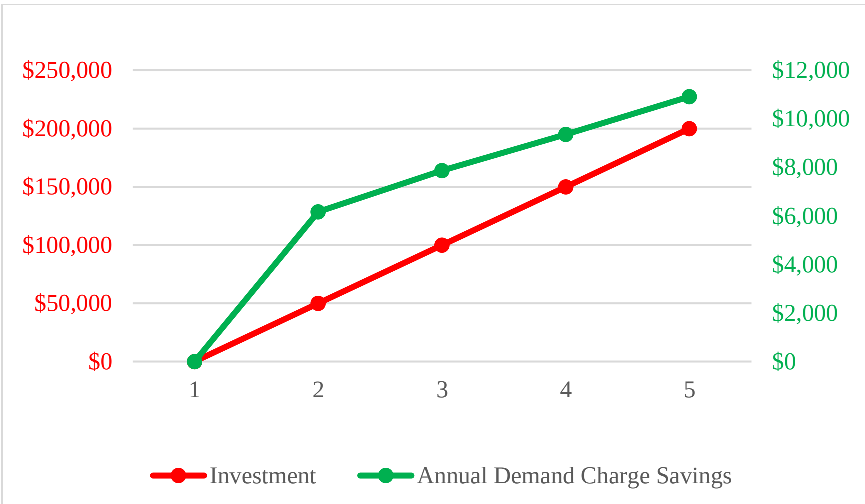


Figure 4.59 Investment and demand charge savings of EEMs

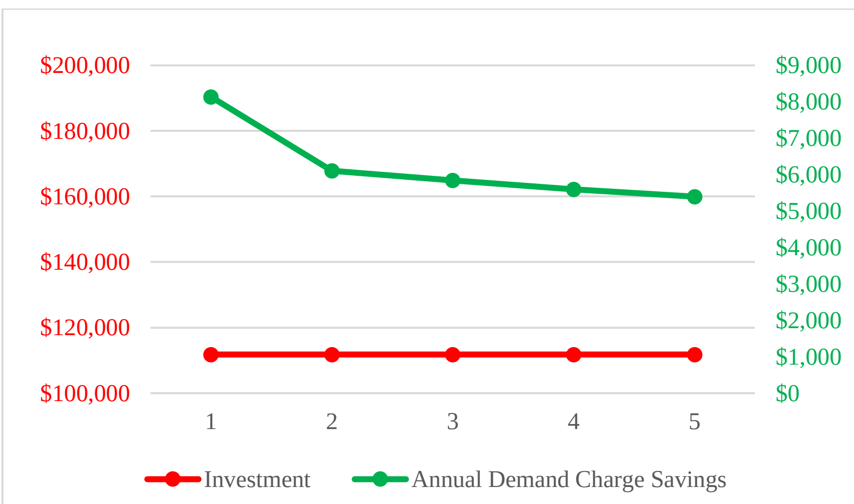


Figure 4.60 Investment and demand charge savings of EFMs

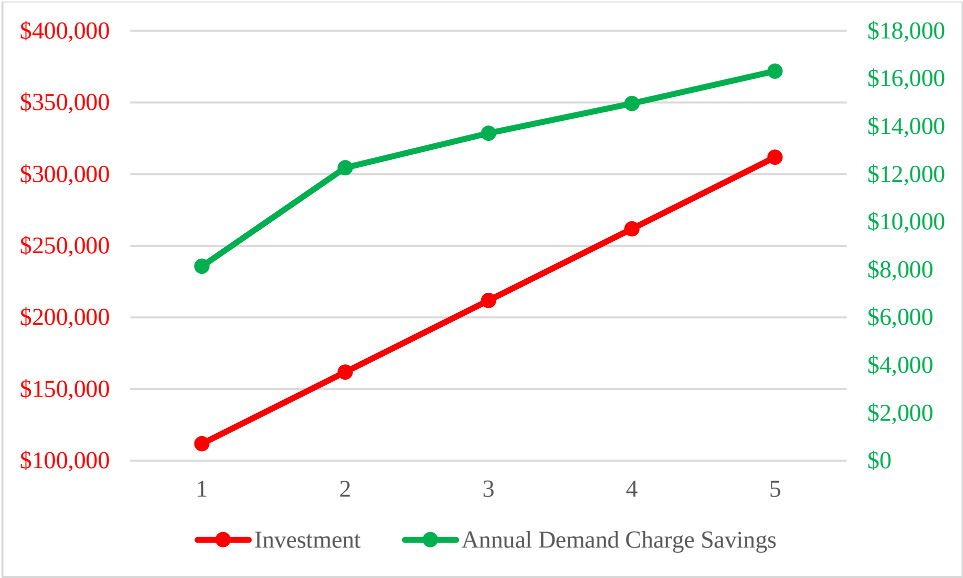


Figure 4.61 Investment and demand charge savings of combined EEM+EFM

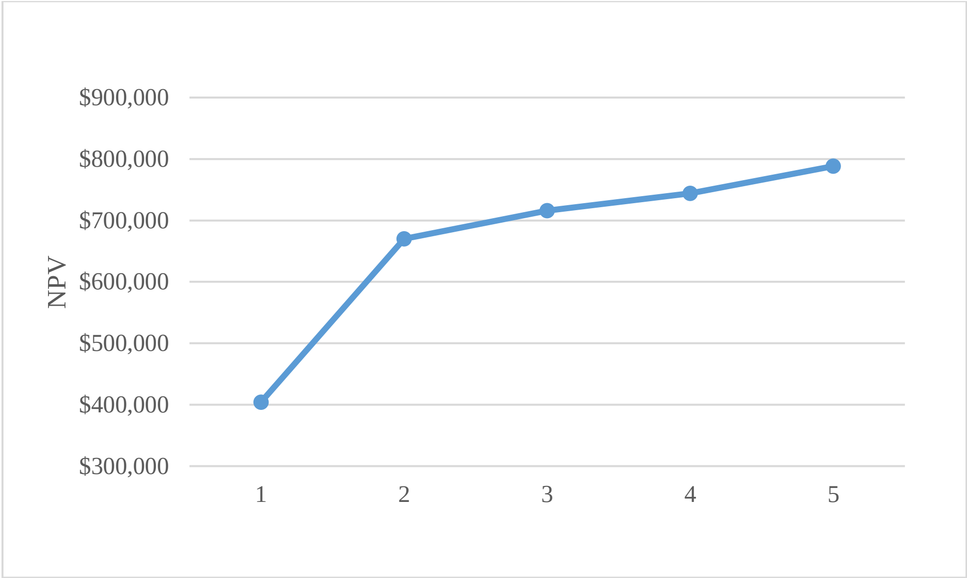


Figure 4.62 NPV results of combined EEM and EFM

NPV results displayed Figure 4.27Figure 4.62 imply that the optimal investment strategy at budget 5 has the maximum investment payback over twenty years. Case 4 and 5 are different options of the same electricity rate schedule that customers can choose from. By comparing the result of case 4 and 5, we can conclude that for the reference hospital building, option B of TOU-GS-3 has a lower monthly utility bill and a higher NPV in twenty years compared to option A.

4.3 Reference Retail Building

The reference retail building is located in Atlanta, GA. The total area is 3000 m^2. The setpoint temperature of the building is 21℃ for heating and 24℃ for cooling. The primary energy source for heating and domestic hot water is natural gas, and the primary energy source for cooling is electricity. The maximum cooling capacity of the chiller is 330 kW. Table 4.23 lists the simulated monthly peak demand and consumption. The summer peak load is 250.93 kW occurring in August. Figure 4.63 illustrates the categorical distribution of annual energy in the hospital building. Lighting and cooling are the top two energy consumers respectively in the prototype retail building.

Table 4.23 Monthly peak demand and energy consumption

	Peak Demand (kW)	Monthly Total Power (kWh)
Jan	127.70	31,860.76
Feb	169.07	33,495.85
Mar	196.83	49,209.65
Apr	202.10	58,217.18
May	216.29	69,236.53
Jun	232.84	73,851.63
Jul	248.09	79,787.43
Aug	250.93	82,579.17
Sep	240.58	66,576.35
Oct	203.72	51,118.79
Nov	156.88	38,808.48
Dec	137.82	31,317.40

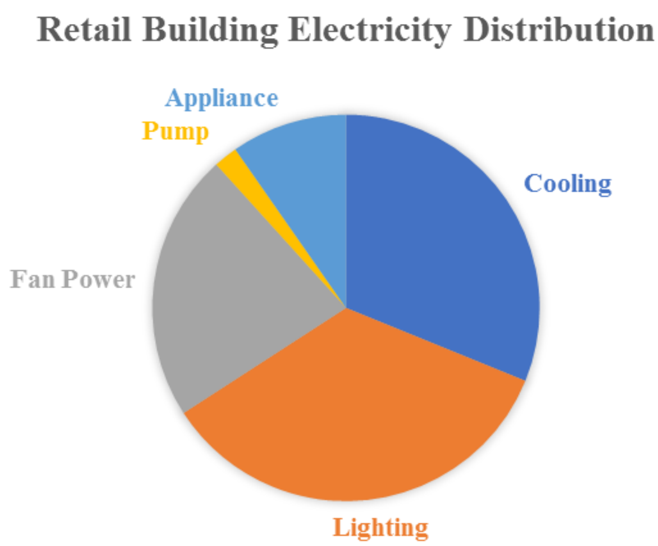


Figure 4.63 Categorical distribution of electricity usage in the hospital building

4.3.1 Sensitivity Analysis

A first order SA is conducted to identify the factor that has the most significant impact on peak demand and total energy consumption of the building in this subsection. The dependency of the peak demand on the chosen variables can best be shown through the resulting distribution of outcomes as a function of the possible variation of input variables. Table 4.24 lists the building parameters, which are assumed to have a value randomly selected from a uniform distribution between a min and max value as given in the table.

A retail building has two different types of occupancy load. One is worker load; the other is customer load. Customer load is different from regular load in commercial buildings. It reaches the peak during evening and weekend and holidays. The retail building also has a large lighting load for the exhibition of products. How much potential do they have by regulating load and lighting are what we want to inspect in this study. Therefore, the optimization factors are listed in

Table 4.24. Temperature control may impact the sale of products, that part of the cost is not counted in the total lost.

Table 4.24 List of optimal variables

<table>
<tr><th rowspan="2"></th><th rowspan="2">Building Parameters</th><th colspan="2">Value</th><th rowspan="2">Cost</th></tr>
<tr><th>Min</th><th>Max</th></tr>
<tr><td rowspan="5">Energy Efficiency Intervention</td><td>Infiltration Rate($m^3/h/m^2$)</td><td>0.2</td><td>0.8</td><td>$4-$10/m</td></tr>
<tr><td>Wall Insulation Thickness (mm)</td><td>0</td><td>100</td><td>$10-$17/m^2</td></tr>
<tr><td>Emissivity of Roof</td><td>0.4</td><td>0.9</td><td>$10-$22/m^2</td></tr>
<tr><td>Solar Reduction Factor</td><td>0.8</td><td>1</td><td>$45-$65/each window</td></tr>
<tr><td>Window SHGC</td><td>0.25</td><td>0.8</td><td>$450-$650/each window</td></tr>
<tr><td rowspan="3">Energy Flexibility Intervention</td><td>Temperature Control</td><td>0</td><td>2.5</td><td>Productivity lost</td></tr>
<tr><td>Lighting Dimmer</td><td>0</td><td>30</td><td>$300/each dimmer</td></tr>
<tr><td>Voltage Throttling</td><td>0</td><td>1</td><td>Productivity lost</td></tr>
<tr><td>Renewable Energy</td><td>Area of the PV System (m^2)</td><td>0</td><td>200</td><td>$520 per m^2</td></tr>
</table>

In the first step, the SA of the billing demand of the building is conducted. Figure 4.64 shows the distribution of the peak demand as the result of varying the EEM/EFM parameters based on the choice of measures, which illustrates that the billing demand can be reduced to 200 kW with the proposed measures, i.e. there are many realizations of measures that will lead to a demand below 200 kW.

Figure 4.65 and Figure 4.66 rank the significance of each parameter in the resulting peak load distribution based on the change in output mean and regression coefficient. In a tornado diagram, the top four bars represent variables that contribute the most to the variability of the outcome and therefore on what the building owner should focus. The top three factors that have the most significant impact on the billing demand are found to be: the SHGC of the window, the solar reduction factor, and the temperature control.

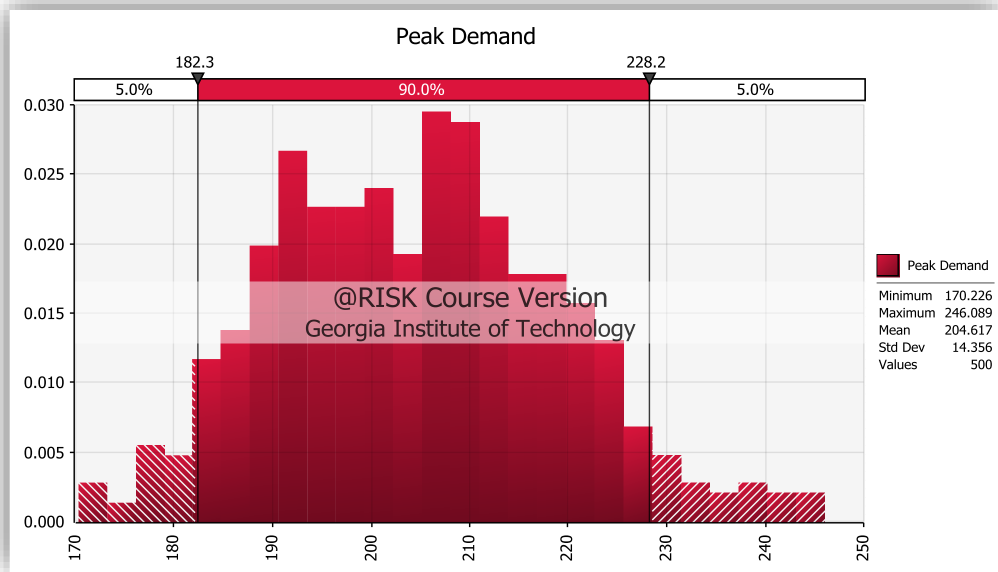


Figure 4.64 Distribution of the peak demand

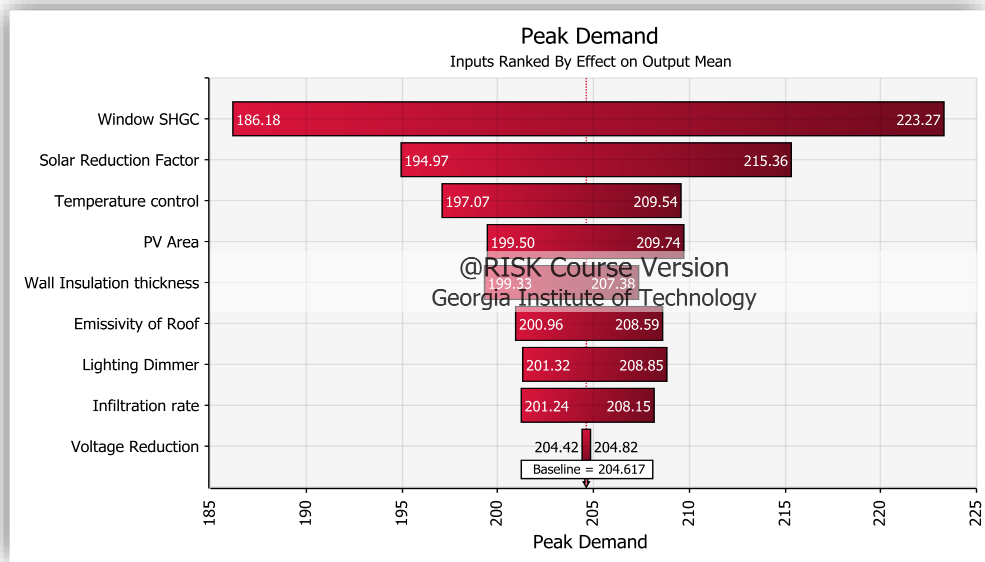


Figure 4.65 SA ranking based on the change in output mean

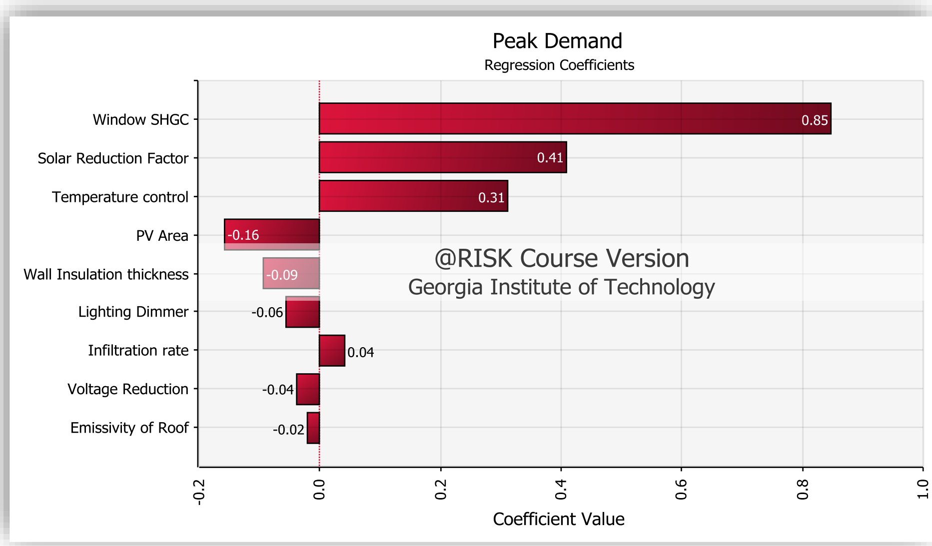


Figure 4.66 SA ranking based on regression coefficient

The second step of the SA is carried out on the coincident peak demand of the building. Figure 4.67 illustrates the distribution of the coincident peak demand as the result of varying EEM/EFM parameters, which imply that the coincident peak demand in the building can be reduced to 120 kW with the proposed optimization factors.

Figure 4.68 and Figure 4.69 rank the significance of each parameter in the resulting coincident peak load distribution based on the change in the output mean and the regression coefficient. The top three factors that have the most significant impact on the coincident peak demand are the temperature control, the window SHGC, and the lighting dimmer.

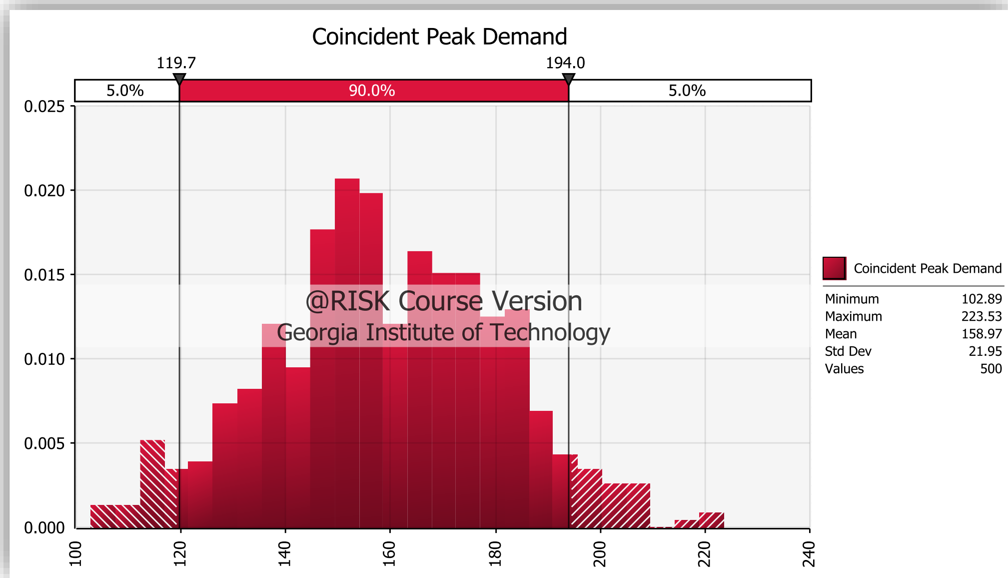


Figure 4.67 Distribution of the coincident peak demand

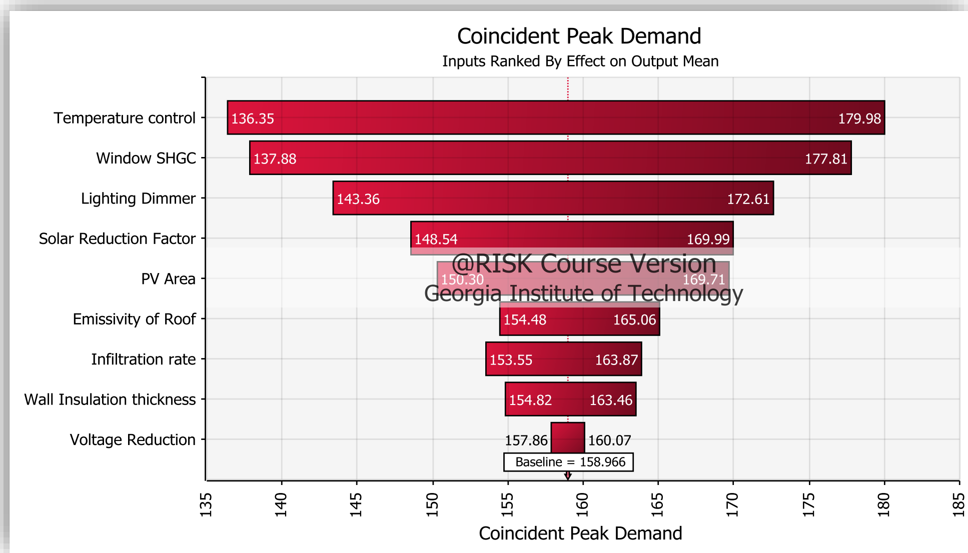


Figure 4.68 SA ranking based on the change in output mean

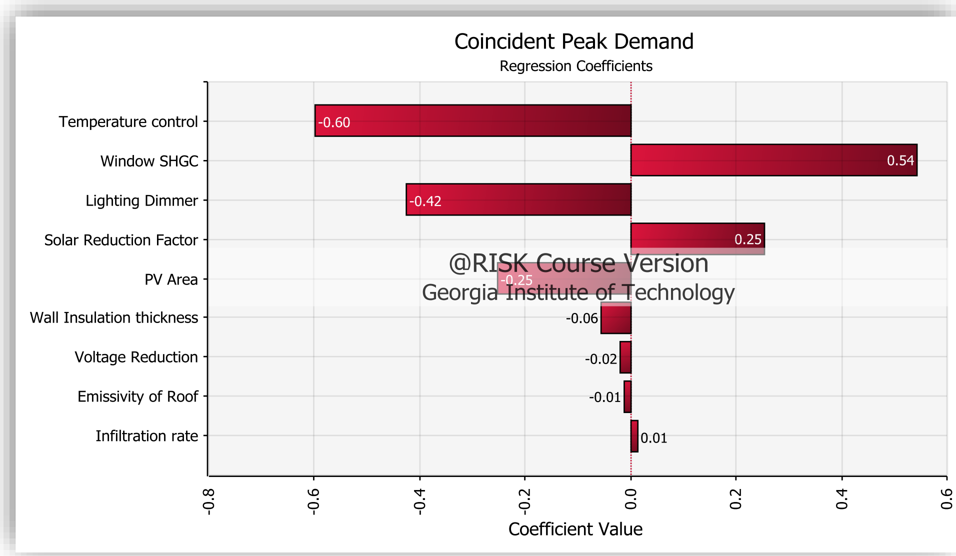


Figure 4.69 SA ranking based on regression coefficient

The last step of the SA is implemented on the total energy consumption of the building. Figure 4.70 shows the distribution of the total energy consumption as the result of varying the EEM/EFM parameters. Figure 4.71 and Figure 4.72 rank the role of each parameter in the resulting total energy consumption distribution based on the change in output mean and regression coefficient. The top three factors that have the most significant impact on the total energy consumption are window SHGC, solar reduction factor and PV area.

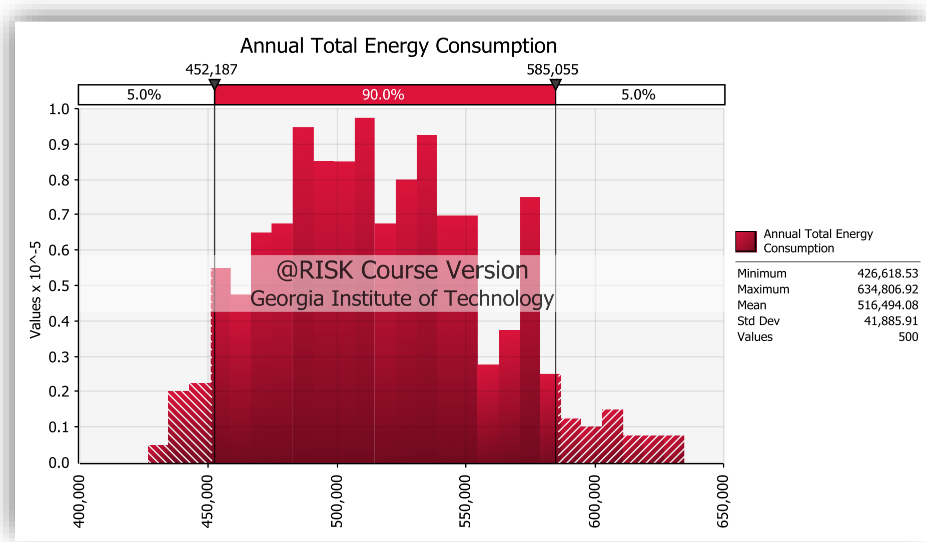


Figure 4.70 Distribution of the total energy consumption

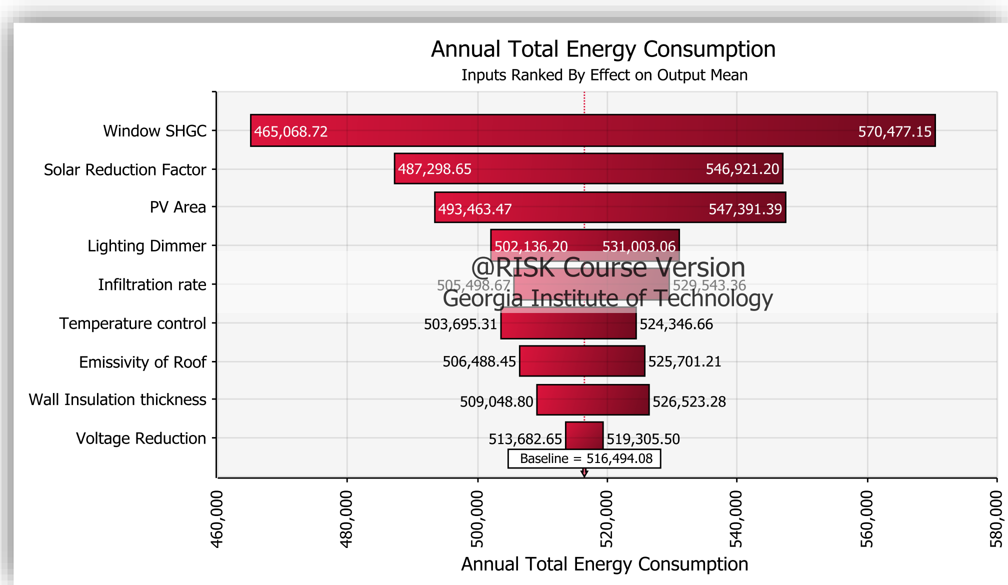


Figure 4.71 SA ranking based on the change in output mean

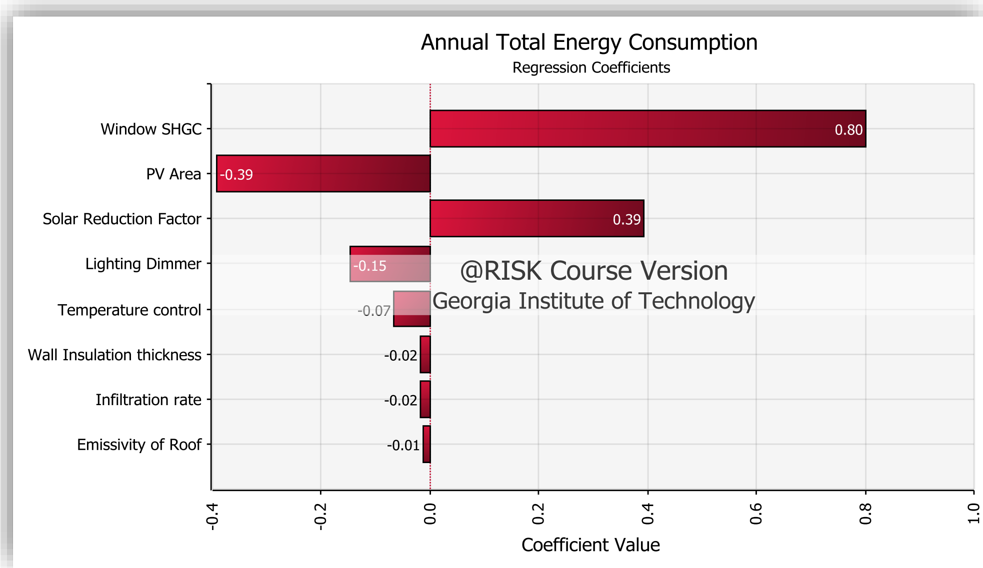


Figure 4.72 SA ranking based on regression coefficient

4.3.2 Case 1: Georgia Power PLM-11

This case adopts the GP's schedule PLM-11 to calculate the cost of electricity and to evaluate the optimal combination of EFMs to reduce demand charges. The case building's peak demand is 250.93 kW, which is difficult to reduce below 30 kW. Therefore, for the case building, demand charges are linearly correlated to the peak demand value in each month under the PLM-11.

The first step is to calculate the monthly electricity cost. Taking the summer month August as an example, the first part is to determine the peak demand in the current month. According to Table 4.23, the peak power in the current month is 250.93 kW. According to PLM-11, this value is higher than the 95% of the highest peak demand in summer months and 60% peak power in winter months, the billing demand power in August is 250.93 kW. The second part is to calculate the HUD in August.

$$\mathrm{HUD} = 82579(\mathrm{kWh})/250.93\ (\mathrm{kW}) = 329$$

The HUD in August is higher than 200 hours but less than 400 hours. According to Appendix A, the electricity price is $0.011437 per kWh. Table 4.25 illustrates the steps to calculate the monthly electricity bill in August.

Table 4.25 Calculation of the monthly electricity bill

Customer Charges	1 month	@	$19.00	$19.00
Demand Charges	250.93 kW	@	$8.24	$2,124.85
Energy Charges	82,579kWh	@	$0.01	$886.04
Subtotal				$3,029.89
ECCR Charges	$3,029.89	@	0.100131	$303.39
NCCR Charges	$3,029.89	@	0.075821	$229.73
FCR Charges	82,579kWh	@	$0.03	$2,690.42
Subtotal				$6,253.43
MFF Charges	$6,253.43	@	0.029109	$182.03
Subtotal				$6,435.46
Sales Tax	$6,435.46	@	7%	$450.48
Total Electric Charges				**$6,885.94**

The optimal combination of EEMs is determined by maximizing the NPV over a 20-year period. Figure 4.73 displays demand charge savings and costs of investment in EEMs at the five budget levels. The red curve represents the investments and the green curve corresponds to annual demand charge savings. Both curves go upward. Budget 2 turns out to have the highest efficiency of investment when only looking at demand charge reduction.

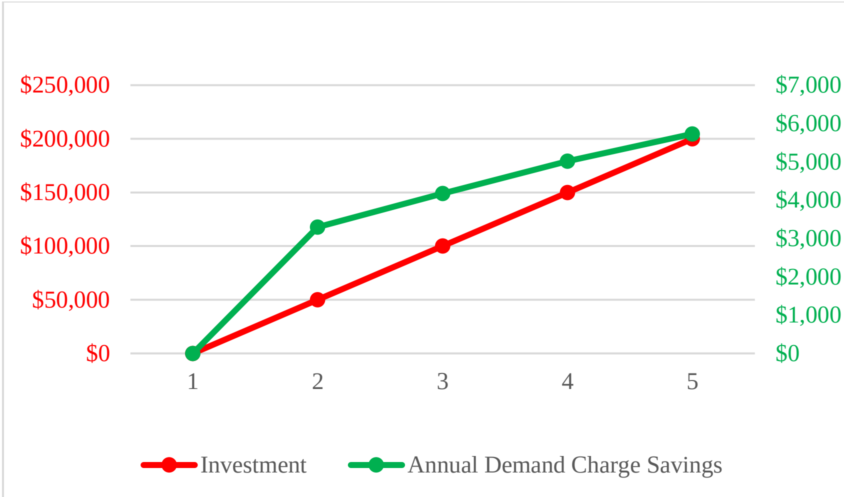


Figure 4.73 Investment and demand charge savings of EEMs

Figure 4.74 shows demand charge savings and investments of implementing the optimal EFMs at each EEM budget level. Budget 5 turns out to have the highest demand charge savings with the same amount of investment in EEMs.

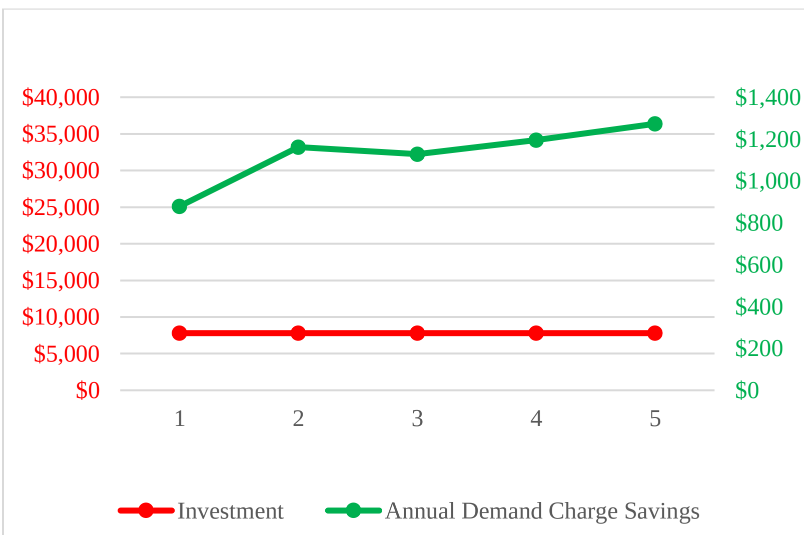


Figure 4.74 Investment and demand charge savings of EFMs

Figure 4.75 shows the total investments and demand charge savings at each EEM budget level. The result reveals that budget 2 has the maximum efficiency of investment in demand charge savings.

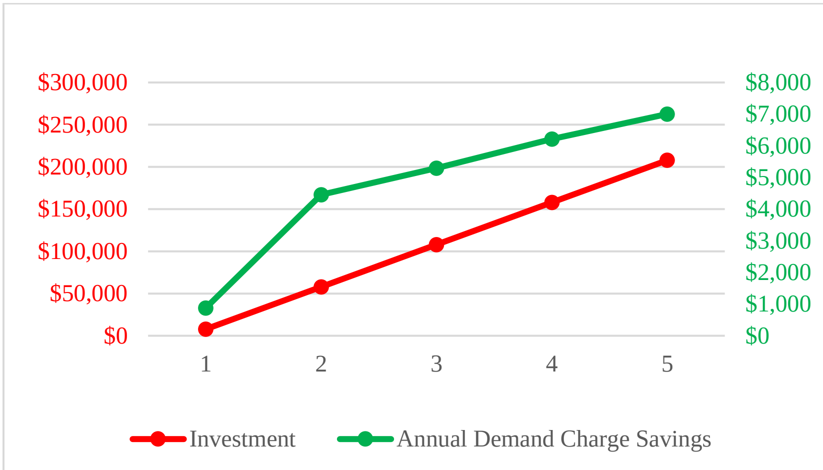


Figure 4.75 Investment and demand charge savings of combined EEM+EFM

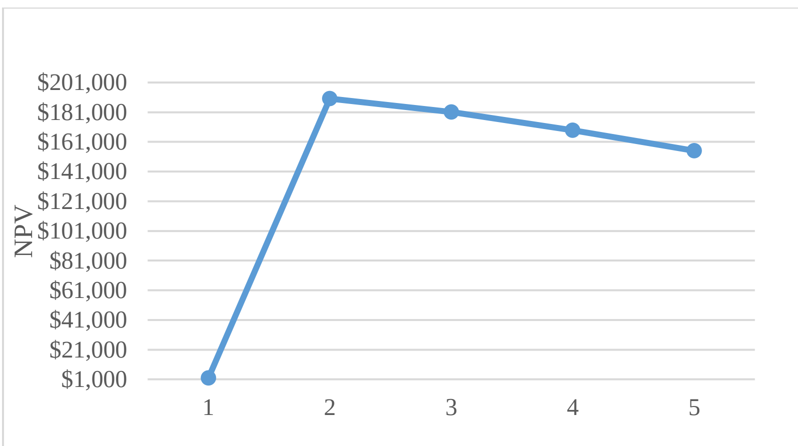


Figure 4.76 NPV results of combined EEM and EFM

The NPV results of Figure 4.76 imply that the optimal investment strategy occurs for budget level 2, as it has the maximum investment payback over twenty years. Increasing the investment budget on EEMs and EFMs does not necessarily lead to a higher NPV in this rate structure.

4.3.3 Case 2: Pacific Gas & Electricity A-10 Non-TOU

This case adopts the PG&E's schedule A-10 non-TOU rates to calculate the cost of electricity and to evaluate the best measure and investment strategy to reduce demand charges. The case building's peak demand is 250.93 kW. If the end user successfully attempts to reduce the peak demand below 200 kW, they could switch to schedule A-1 for small general service, which has the same energy rate as A-10, but no demand charge.

The first step is to calculate the monthly electricity bill. Taking the summer month August as an example, the first part is to decide the peak demand in the current month. The customer will be billed for demand according to the customer's maximum demand, which equals to the highest 15-minute average in the month. According to Table 4.23, the billing demand in August is 250.93 kW. Appendix B lists the rate structure of schedule A-10 non-TOU rate. Table 4.26 details the steps to calculate the monthly electricity bill in August.

Table 4.26 Calculation of the monthly electricity bill

Customer Charge	31 days	@	$4.60	$142.59
Demand Charges	250.93 kW	@	$16.78	$5,101.12
Energy Charges	82,579kWh	@	$0.14	$11,561.06
Transmission Rate Adjustments	82,579kWh	@	$0.00	$389.77
Public Purpose Programs	82,579kWh	@	$0.01	$1,169.32
Nuclear Decommissioning	82,579kWh	@	$0.00	$123.04
Competition Transition Charges	82,579kWh	@	$0.00	$82.58
DWR Bond	82,579kWh	@	$0.01	$453.36
New System Generation Charge	82,579kWh	@	$0.00	$196.54
Subtotal				$19,219.38
Sales Tax	$19,219.38	@	7%	$1,345.36
Total Electric Charges				$20,564.74

Figure 4.77 displays demand charge savings and investments of implementing optimal EEMs at each EEM budget level. There is a sharp rise at budget 4 because executing EEMs can

successfully reduce the peak demand below 200 kW, at which point no demand charge will be applied to the building.

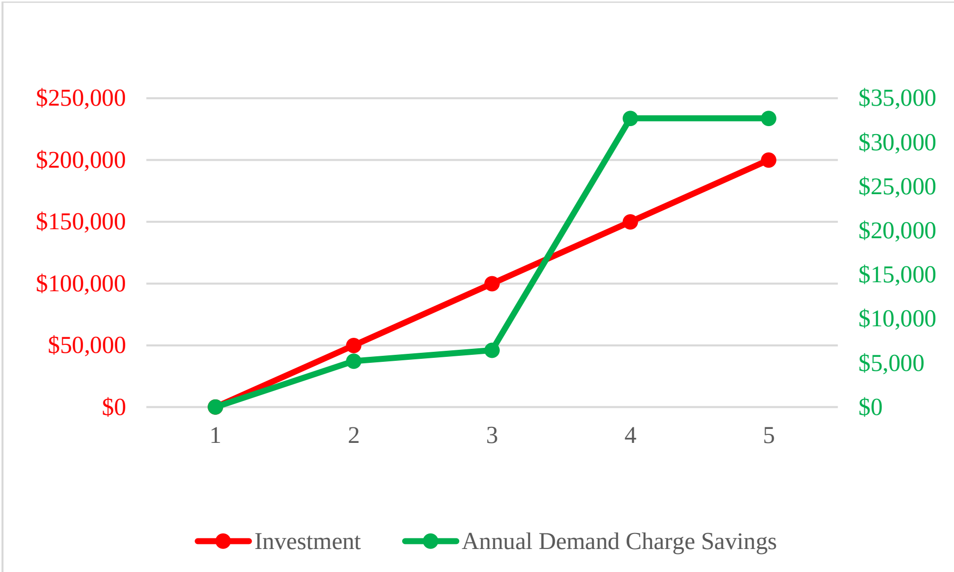


Figure 4.77 Investment and demand charge savings of EEMs

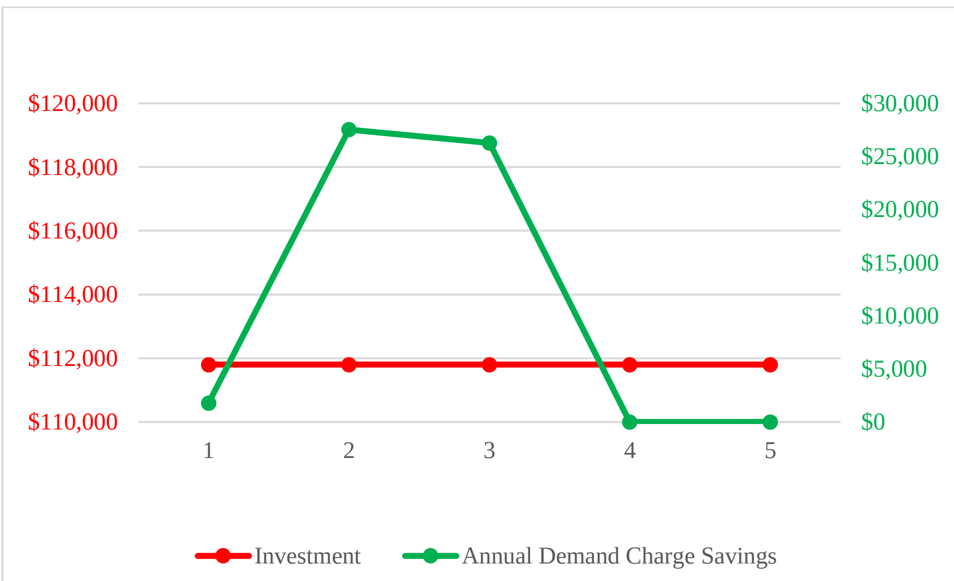


Figure 4.78 Investment and demand charge savings of EFMs

Figure 4.78 shows demand charge savings and investments of implementing the optimal EFMs at each EEM budget level. Investments are identical at each EEM budget level. The curve of annual demand charge savings rises at budget 2 and 3 and declines at budget 4. Because executing EFMs can successfully reduce the peak demand below 200 kW at budget 2 and 3. However, in budget 4 and 5, the EEM package can reduce the peak demand below 200 kW. There's no room left for demand charge reduction through EFMs in these higher budget levels.

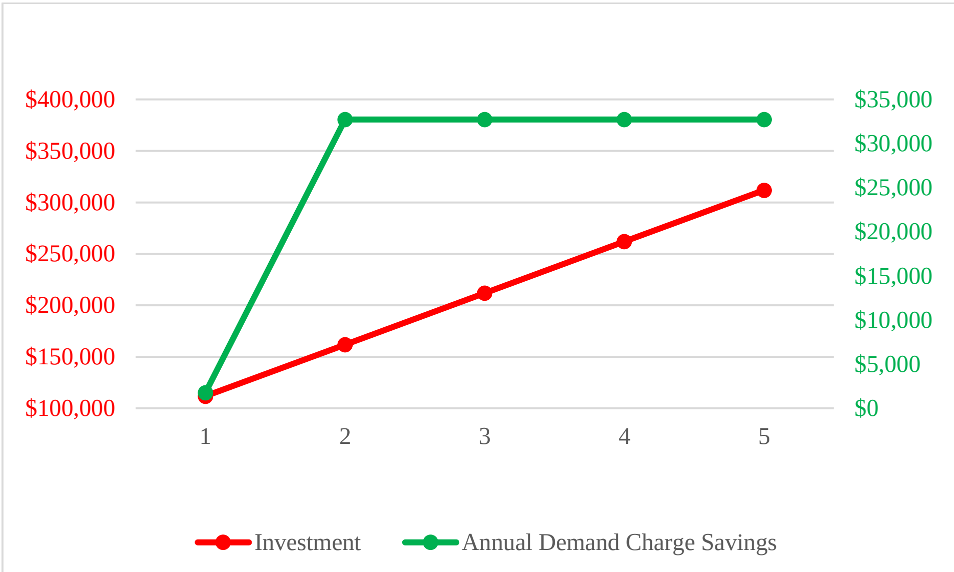


Figure 4.79 Investment and demand charge savings of combined EEM+EFM

Figure 4.79 depicts the change of total investment cost and demand charge savings for each budget. The demand charge saving curve remains steady between budget 2 to 5 because the maximum demand charge reduction has been achieved at these levels.

Figure 4.80 displays the NPV in five budgets in twenty years. Although the optimization result suggests that budget 5 has the maximum NPV, the NPV does not vary too much from budget 2 to 5. Considering the $150,000 difference in the initial budget at budget 2 and 5, the customer may want to choose the investment strategy suggested at budget 2.

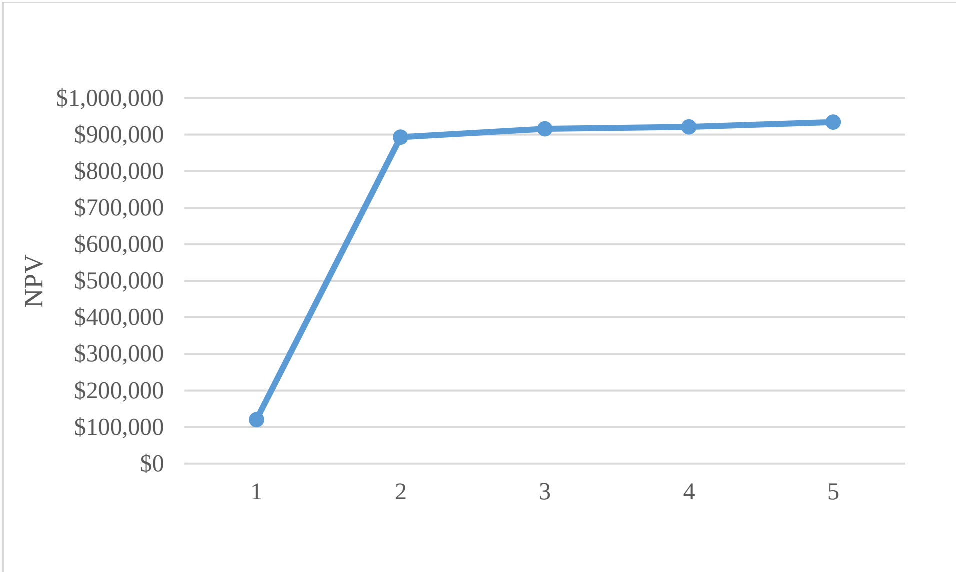


Figure 4.80 NPV results of combined EEM and EFM

4.3.4 Case 3: Pacific Gas & Electricity A-10 TOU

This case employs the PG&E's schedule A-10 TOU rates to calculate the cost of electricity and to evaluate the best measure and investment strategies to reduce demand charges. Different from the flat daily rate structure in case 2, the schedule A-10 TOU adopts a TOU rate structure. Table 2.1 and Table 4.3 details how times of the day are defined and how much is the hourly rate during a day. This rate schedule also includes the PDP rate. In a PDP event day, the customer will be charged $0.9 per kWh from 12 p.m. to 4 p.m. In contrast, they will receive a credit of $3.26 per kW reduction on peak demand in the month that contains the PDP event. Section 4.1 has introduced how to decide the PDP event day. This case adopts the same method and Table 4.27Table 4.19Table 4.11 lists the selection criteria and the date of days that meet the criteria.

Table 4.27 Number of days meets the criteria

T>35.9 ℃	July 8
T>34.9 ℃	July 7, 14, August 1, 2, 18
T>33.9 ℃	June 6, 13, July 6, 9, 13, 21

The first step is to calculate the monthly electricity bill. Taking the summer month August as an example, the first part is to decide the peak demand in the current month. The customer will be billed for demand according to the customer's maximum demand, which equals to the highest 15-minute average in the month. According to Table 4.23, the billing demand in August is 250.93 kW. Table 4.28 details the steps to calculate the monthly electricity bill in August. The total amount to be paid by the building in August is $24,748.73. It is worth mentioning that the rate structure in case 2 and 3 both apply to PG&E's customers with peak demand greater than 200 kW but less than 499 kW. By comparing the monthly electricity charge in case 2 and 3, we find out that for the reference retail building, before applying any EFM or EEM, choosing the non-TOU rate has a relative low electricity cost.

Table 4.28 Calculation of the monthly electricity bill

Customer Charge	31 days	@	$4.60	$142.59
Demand Charges	250.93 kW	@	$16.78	$4,210.61
Subtotal				$4,353.19
On-Peak	26569.65 kWh	@	$0.22	$5,837.88
Partial-Peak	26231.54 kWh	@	$0.16	$4,317.45
Off-Peak	26973.41 kWh	@	$0.14	$3,682.41
PDP Events	2804.56 kWh	@	$0.90	$2,524.10
Total Energy Charges	82579 kWh			$16,361.85
Transmission Rate Adjustments	82579 kWh	@	$0.00472	$389.77
Public Purpose Programs	82579 kWh	@	$0.01416	$1,169.32
Nuclear Decommissioning	82579 kWh	@	$0.00149	$123.04
Competition Transition Charges	82579 kWh	@	$0.00100	$82.58
DWR Bond	82579 kWh	@	$0.00549	$453.36
New System Generation Charge	82579 kWh	@	$0.00238	$196.54
Subtotal				$23,129.65
Sales Tax	$23,129.65	@	7%	$1,619.08
Total Electric Charges				$24,748.73

Figure 4.81 demand charge savings and investment costs of implementing the optimal EFMs at each budget level. Among five budgets, budget 5 has the highest demand charge savings.

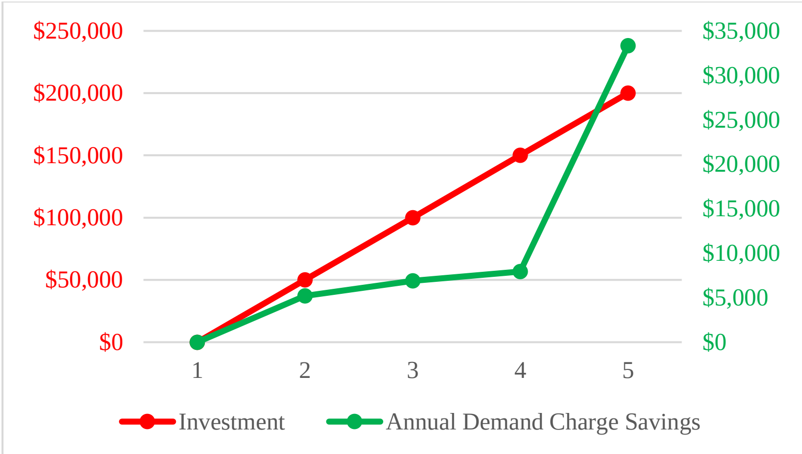


Figure 4.81 Investment and demand charge savings of EEMs

Figure 4.82 details demand charge savings and investments of implementing the optimal EFMs at each EEM budget level. The investment cost curve remains steady with increasing budget. The curve of annual demand charge savings rises at budget 3 and 4 and declines at budget 5. Because executing EFMs can successfully reduce the peak demand below 200 kW in budget 3 and 4. However, at budget 5, the EEM package can reduce the peak demand below 200 kW. There’s no room left for demand charge reduction through EFMs at this budget level.

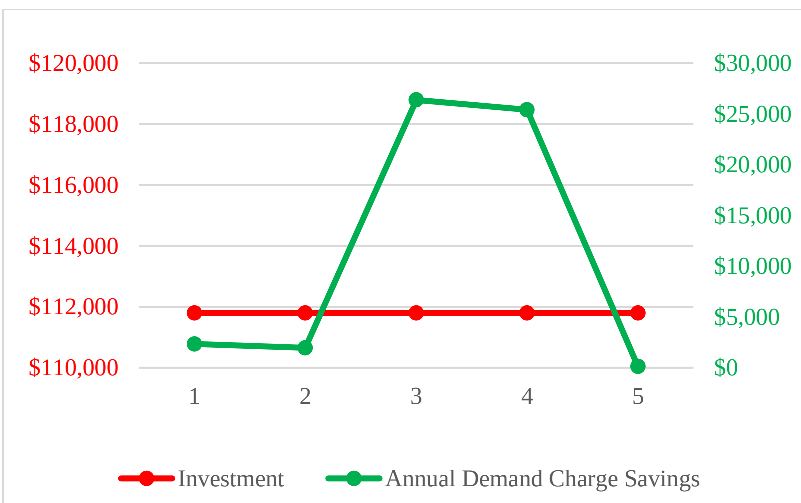


Figure 4.82 Investment and demand charge savings of EFMs

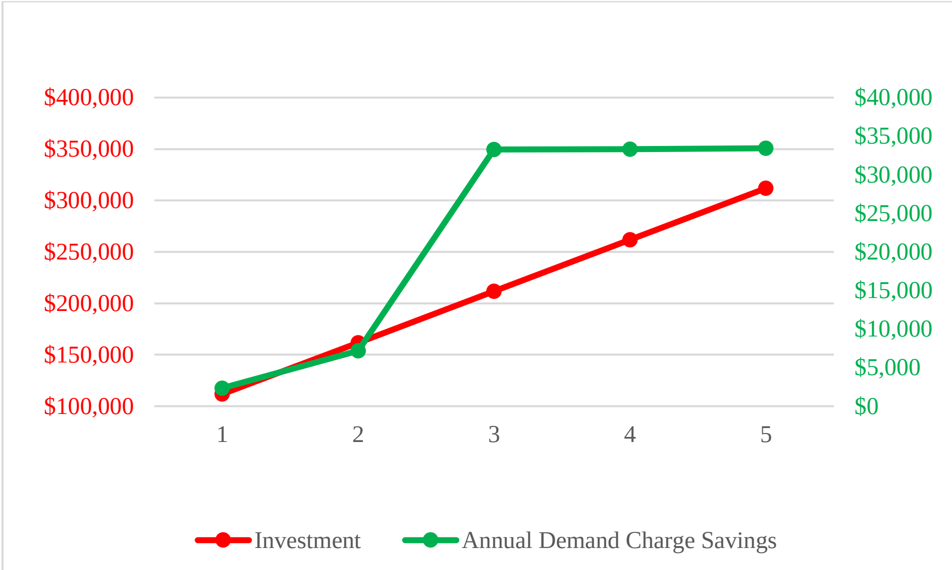


Figure 4.83 Investment and demand charge savings of combined EEM+EFM

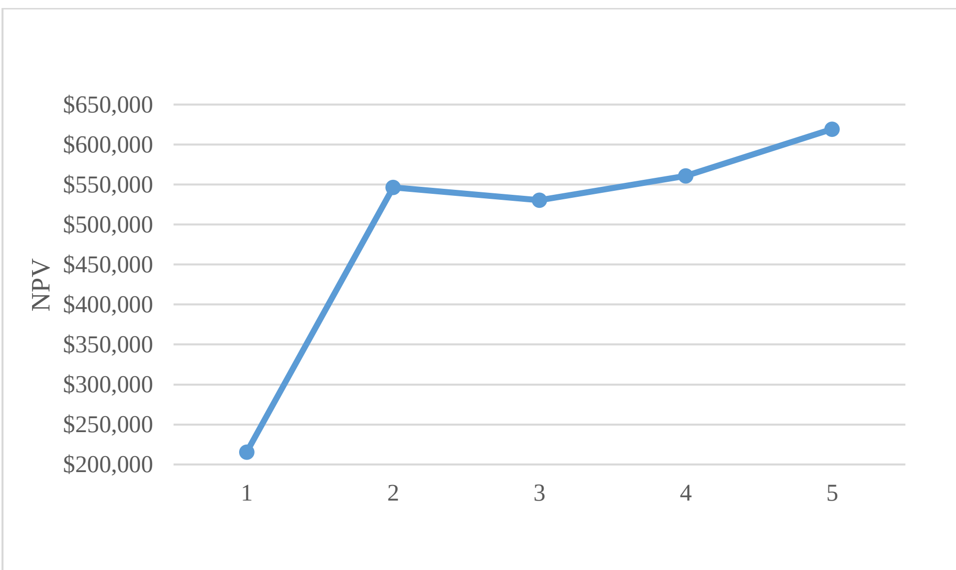


Figure 4.84 NPV results of combined EEM and EFM

Figure 4.83 illustrates the total investment and demand charge savings at each EEM budget level. Budget levels 3, 4 and 5 achieve the highest demand charge savings. The NPV results in Figure 4.84 imply that the optimal investment strategy at budget 5 has the maximum investment payback over twenty years. Case 2 and 3 are different options of the same electricity rate schedule that customers can choose from. In both cases, the optimization result suggests that the peak demand can reduce below 200 kW, which indicates that the financial benefit of reduced demand charges exceeds the rise in the energy price. By comparing the result of case 2 and 3, we can conclude that for the reference retail building, the non-TOU rate has a higher NPV in twenty years compared to the TOU rate.

4.3.5 Case 4: Southern California Edison TOU-GS-3 Option A

This case adopts the Southern California Edison's schedule TOU-GS-3 option A rates to calculate the cost of electricity and to evaluate the best measures and investment strategy to reduce demand charges. The case building's peak demand is 250.93 kW. If the end user successfully attempts to reduce the peak demand below 200 kW, they could switch to schedule TOU-GS-2 option A, which has a higher energy rate, but a lower demand charge. Therefore, if the results show that demand charges contribute a lot in the electricity bill, the end user should make a serious effort to bring the peak demand below 200 kW.

The first step is to calculate the monthly electricity bill. Taking the summer month August as an example, the first part is to decide the peak demand in the current month. The customer will be billed for demand according to the customer's maximum demand, which equals to the highest 15-minute average in the month. According to Table 4.23, the billing demand in August is 257.87 kW. Table 4.29 details the steps to calculate the monthly electricity bill in August. The total amount to be paid by the building in August is $20,157.53.

Table 4.29 Calculation of the monthly electricity bill

Customer Charge		1 month	@	$466.13	$466.13
Demand Charges		250.93 kW	@	$17.81	$4,469.06
Subtotal					$4,935.19
	On-Peak	29374.21 kWh	@	$0.32	$9,399.75
	Partial-Peak	26231.54 kWh	@	$0.11	$2,885.47
	Off-Peak	26973.41 kWh	@	$0.06	$1,618.40
Total Energy Charges		82579 kWh			$13,903.62
Subtotal					$18,838.81
Sales Tax		$18,838.81	@	7%	$1,318.72
Total Electric Charges					$20,157.53

Figure 4.85, Figure 4.86, and Figure 4.87 show demand charge savings and investments of implementing the optimal EEMs, EFMs and combined measures together at the five budget levels. The result from these analyses reveals that the optimal investment strategy suggested at budget 5 achieves the maximum demand charge savings.

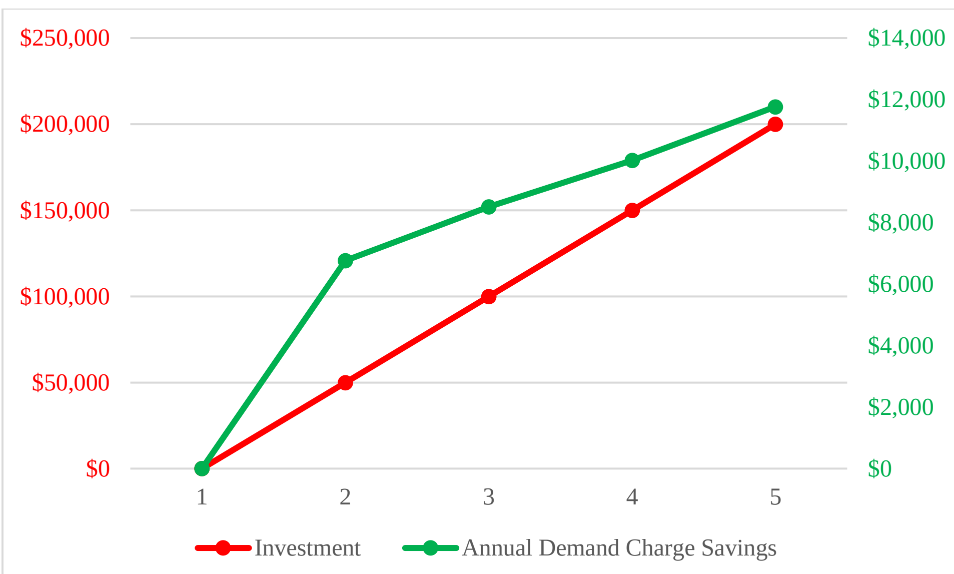


Figure 4.85 Investment and demand charge savings of EEMs

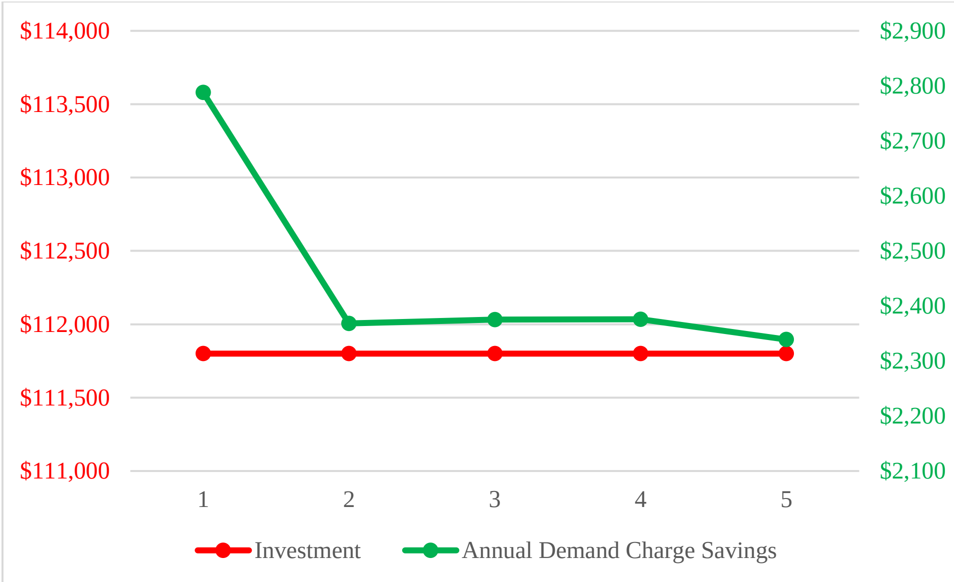


Figure 4.86 Investment and demand charge savings of EFMs

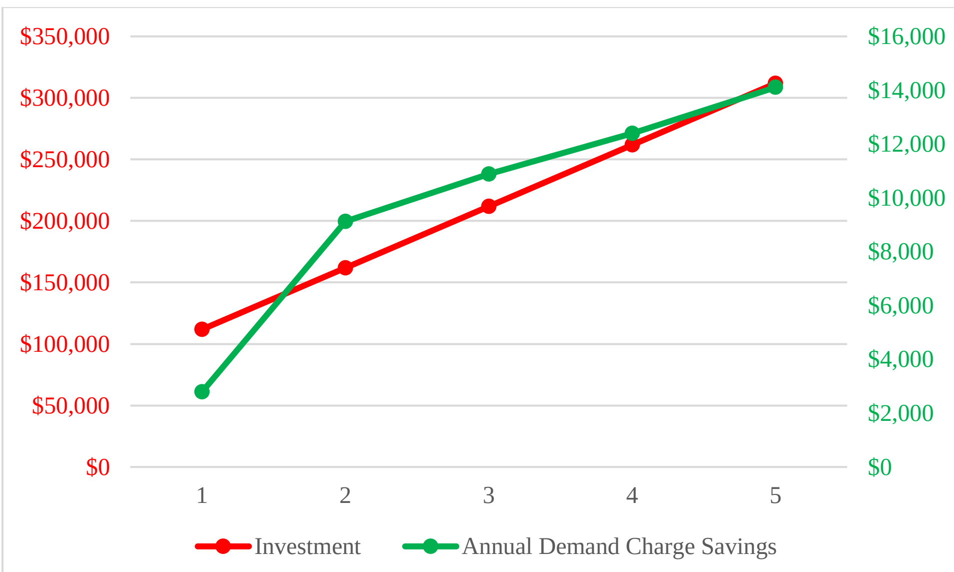


Figure 4.87 Investment and demand charge savings of combined EEM+EFM

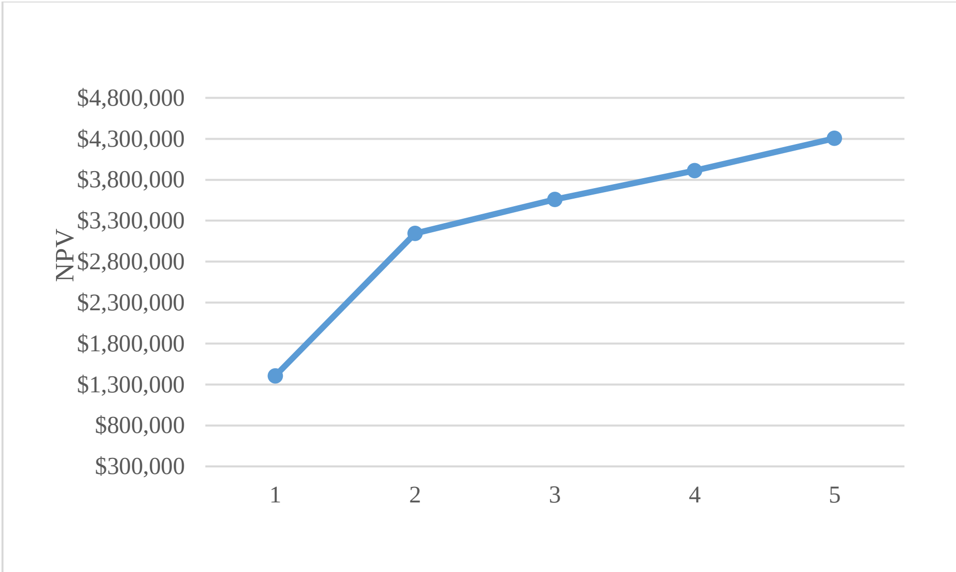


Figure 4.88 NPV results of combined EEM and EFM

The NPV results displayed in Figure 4.88 imply that the optimal investment strategy at budget 5 has the maximum investment payback over twenty years. The optimal EEM and EFM package brings the peak demand down below 200 kW. Although TOU-GS-2 option A has a higher energy rate, the result of the optimization analysis suggests that the financial benefit of reduced demand charges exceeds the rise in the energy price.

4.3.6 Case 5: Southern California Edison TOU-GS-3 Option B

This case adopts the Southern California Edison's schedule TOU-GS-3 option B rates to calculate the cost of electricity and to evaluate the best measures and investment strategy to reduce demand charges. The case building's peak demand is 250.93 kW. If the end user successfully attempts to reduce the peak demand below 200 kW, they could switch to schedule TOU-GS-2 option B, which has a higher energy rate, but a lower demand charge.

The first step is to calculate the monthly electricity bill. The customer will be billed for facility related demand and time-related demand, which includes on-peak and partial-peak demand. Table 4.30 details the steps to calculate the monthly electricity bill in August. The total amount to be paid by the building in August is $18,541.84.

Table 4.30 Calculation of the monthly electricity bill

Customer Charge		1 month	@	$466.13	$466.13
	Facility	250.93 kW	@	$17.81	$4,469.06
	On-Peak	250.93 kW	@	$17.42	$4,371.20
	Partial-Peak	227.58 kW	@	$3.43	$780.60
Total Demand Charges					$9,620.86
Subtotal					$10,086.99
	On-Peak	29374.21 kWh	@	$0.12	$3,524.91
	Partial-Peak	26231.54 kWh	@	$0.08	$2,098.52
	Off-Peak	26973.41 kWh	@	$0.06	$1,618.40
Total Energy Charges					$7,241.83
Subtotal		82579 kWh			$17,328.83
Sales Tax		$17,328.83	@	7%	$1,213.02
Total Electric Charges					$18,541.84

It is worth mentioning that case 4 and 5 both apply to SCE's customers with peak demand greater than 200 kW but less than 500 kW. The customer can choose which option they want to enroll in. By comparing the monthly electricity charge in case 4 and 5, we could draw the conclusion that for the reference retail building, before applying any EFM or EEM, choosing the TOU-GS-3 option B with time-related demand and DR incentive has a lower electricity bill.

Figure 4.89, Figure 4.90, and Figure 4.91 show demand charge savings and investments of implementing the optimal EEMs, EFMs, and combined measures at each EEM budget level. The result from these analyses reveals that the optimal investment strategy suggested at the budget level 5 achieves the maximum demand charge savings.

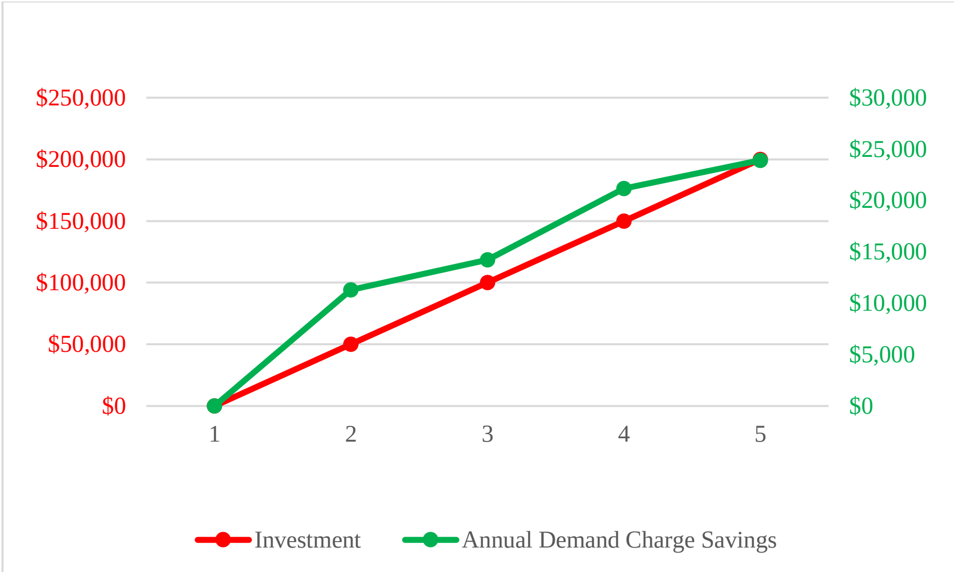


Figure 4.89 Investment and demand charge savings of EEMs

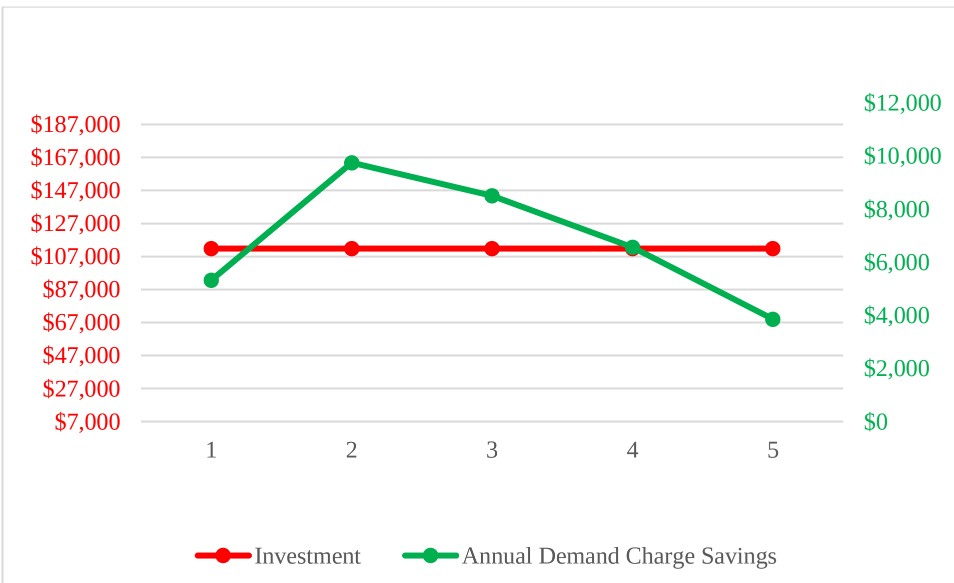


Figure 4.90 Investment and demand charge savings of EFMs

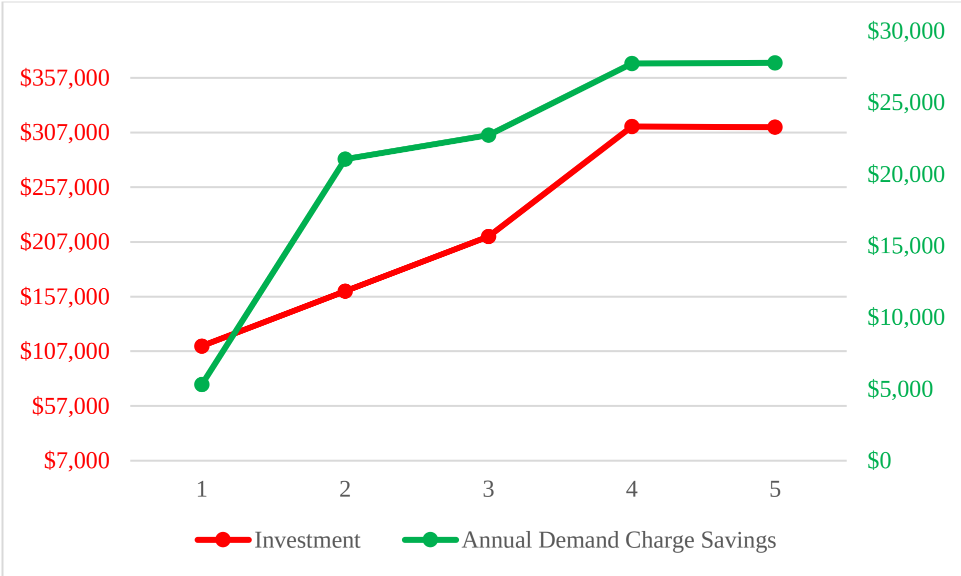


Figure 4.91 Investment and demand charge savings of combined EEM+EFM

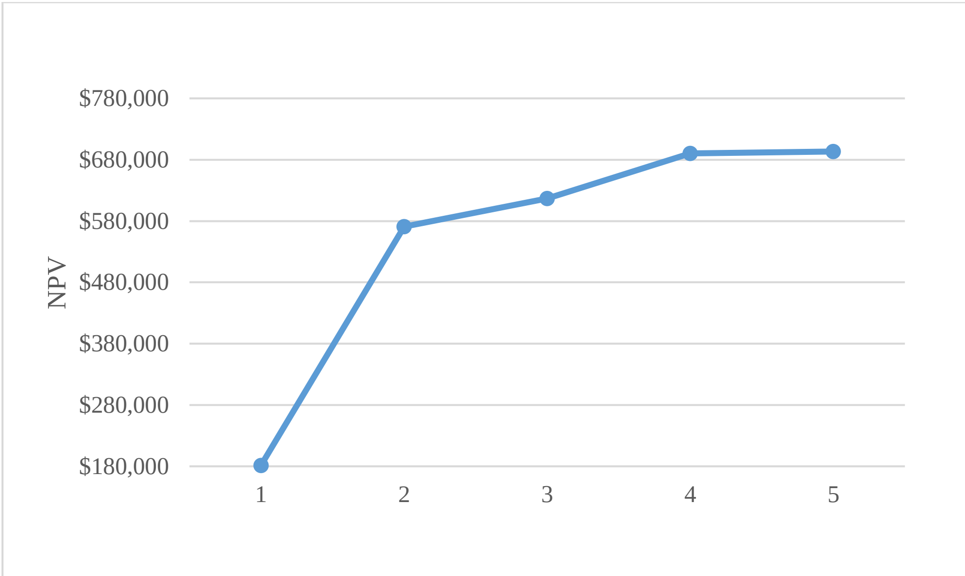


Figure 4.92 NPV results of combined EEM and EFM

The NPV results displayed Figure 4.27Figure 4.92 imply that the optimal investment strategy at budget 5 has the maximum investment payback over twenty years. Case 4 and 5 are options of the same electricity rate schedule that customers can choose from. By comparing the result of case 4 and 5, we can conclude that for the reference retail building, option B of TOU-GS-3 has a lower monthly utility bill and a higher NPV in twenty years compared to option A.

4.4 Summary of Deterministic Analysis

This section summarizes the deterministic case studies in this Chapter. Table 4.31, Table 4.32, and Table 4.33 detail the investment in the three types of commercial buildings that were analyzed. Moreover, it shows for all budget levels and rate structures which EEM and EFM were chosen in the optimal package.

In office buildings, cooling and lighting are two dominant energy consumers. For the EEMs, roof emissivity, solar reduction factor, and window SHGC are selected in all optimizations, although in some optimizations the achievement level is low due to the limited budget. The infiltration rate and insulation thickness are only recommended at certain budget level. In case 5 budget 3 of the office building, the optimal value of the thickness of the R-20 insulation material is 15 mm, which gives the maximum NPV in twenty years. The NPV is affected by both the investment and the energy cost. Increasing thickness of the R-20 will increase the investment, but reduce the demand charges during the summer season. Because the peak demand usually occurs when the outside temperature is high, improving the insulation of the building can reduce the transmittance heat gain from the outside, therefore reducing the power demand.

The hospital building has the highest peak demand of the three types of buildings that were analyzed in this chapter. In a hospital building, cooling and appliance are the top two energy consumers. Therefore, schedule adjustment is selected in the optimal set in all cases, since it shifts considerable appliance load from on-peak hours to off-peak hours. The setpoint temperature control is recommended in all cases. Because the cooling setpoint in the hospital is 21℃, increasing the thermostat by 2.5 ℃ will under normal circumstances lead to thermal discomfort which implies that setpoint control is an EFM that has no penalty. Obviously, this will need more detailed analysis, looking at different zones and different temperature ranges mandated for different clinical processes. This, however, is outside the scope of this thesis.

In a retail building, lighting and cooling are the top two energy consumers. The peak cooling in a building usually occurs during afternoon hours of hot summer days. However, the retail building usually reaches the maximum operation load during the late afternoon and early evening hours on weekdays, and during the whole day on weekends. Therefore, the retail building has a moderate peak demand and a gentle load profile compared to the other two types of commercial buildings.

Table 4.31 Investment in the office building

Deterministic Analysis		EEMs					EFMs			
		Infiltration Rate	Insulation Thickness	Emissivity of Roof	Solar Reduction Factor	Window SHGC	Temperature Control	Lighting Dimmer	Voltage Throttling	PV System
Case 1	Budget 1	-	-	-	-	-	-	$7,800	Yes	$40,560
	Budget 2	-	$2,400	$7,500	$24,200	$15,900	-	$1,300	Yes	-
	Budget 3	-	$4,300	$7,500	$24,200	$64,000	-	$7,800	Yes	-
	Budget 4	-	$5,800	$7,500	$24,200	$112,500	-	$7,800	-	-
	Budget 5	$9,700	$12,800	$7,500	$24,200	$145,800	-	$7,800	-	-
Case 2	Budget 1	-	-	-	-	-	Yes	$7,800	Yes	$104,000
	Budget 2	-	-	$7,500	$24,200	$18,300	Yes	$7,800	Yes	$104,000
	Budget 3	-	-	$7,500	$24,200	$68,300	Yes	$7,800	-	$104,000
	Budget 4	-	-	$7,500	$24,200	$118,300	Yes	$7,800	-	$104,000
	Budget 5	-	$1,800	$7,500	$24,200	$166,500	Yes	$7,800	-	$104,000
Case 3	Budget 1	-	-	-	-	-	Yes	$7,800	-	$104,000
	Budget 2	-	-	$7,500	$24,200	$18,300	Yes	$7,800	-	$104,000
	Budget 3	-	-	$7,500	$24,200	$68,300	Yes	$7,800	-	$104,000
	Budget 4	-	$900	$7,500	$24,200	$117,400	Yes	$7,800	-	$104,000
	Budget 5	-	$2,500	$7,500	$24,200	$165,800	Yes	$7,800	-	$104,000
Case 4	Budget 1	-	-	-	-	-	Yes	$7,800	-	$104,000
	Budget 2	-	-	$7,500	$24,200	$18,300	Yes	$7,800	-	$104,000
	Budget 3	-	-	$7,500	$24,200	$68,300	Yes	$7,800	-	$104,000
	Budget 4	-	-	$7,500	$24,200	$118,300	Yes	$7,800	-	$104,000
	Budget 5	-	-	$7,500	$24,200	$168,300	Yes	$7,800	-	$104,000
Case 5	Budget 1	-	-	-	-	-	Yes	$7,800	Yes	$104,000
	Budget 2	-	$1,200	$7,500	$24,200	$17,100	Yes	$7,800	Yes	$104,000
	Budget 3	-	$2,700	$7,500	$24,200	$65,600	Yes	$7,800	-	$104,000
	Budget 4	-	$3,100	$7,500	$24,200	$115,200	Yes	$7,800	-	$104,000
	Budget 5	-	$3,500	$7,500	$24,200	$164,800	-	$7,800	-	$104,000

Table 4.32 Investment in the hospital building

Deterministic Analysis		EEMs					EFMs				
		Infiltration Rate	Insulation Thickness	Emissivity of Roof	Solar Reduction Factor	Window SHGC	Temperature Control	Lighting Dimmer	Voltage Throttling	Schedule Adjustment	PV System
Case 1	Budget 1	-	-	-	-	-	Yes	-	Yes	Yes	-
	Budget 2	$5,000	$7,100	$4,100	$24,200	$9,600	Yes	-	Yes	Yes	$4,680
	Budget 3	$4,000	$4,800	$3,000	$24,200	$64,000	Yes	-	Yes	Yes	$28,600
	Budget 4	$7,200	$2,300	$1,100	$23,600	$115,200	Yes	-	Yes	Yes	-
	Budget 5	$1,000	$1,000	$2,200	$23,000	$172,800	Yes	-	Yes	Yes	-
Case 2	Budget 1	-	-	-	-	-	Yes	$7,800	Yes	Yes	$104,000
	Budget 2	$6,600	$2,900	$4,100	$23,600	$12,800	Yes	$7,800	Yes	Yes	$104,000
	Budget 3	$4,000	$4,800	$3,000	$24,200	$64,000	Yes	$7,800	Yes	Yes	$104,000
	Budget 4	$7,200	$2,900	$1,100	$23,600	$115,200	Yes	$7,800	Yes	Yes	$104,000
	Budget 5	$4,800	$4,800	$3,000	$24,200	$163,200	Yes	$7,800	Yes	Yes	$104,000
Case 3	Budget 1	-	-	-	-	-	Yes	$7,800	Yes	Yes	$104,000
	Budget 2	$4,400	$3,800	$3.400	$22,400	$16,000	Yes	$7,800	Yes	Yes	$104,000
	Budget 3	$4,000	$4,800	$3,000	$24,200	$64,000	Yes	$7,800	Yes	Yes	$104,000
	Budget 4	$7,200	$2,900	$1,100	$23,600	$115,200	Yes	$7,800	Yes	Yes	$104,000
	Budget 5	$4,800	$4,800	$3,000	$24,200	$163,200	Yes	$7,800	Yes	Yes	$104,000
Case 4	Budget 1	-	-	-	-	-	Yes	$7,800	Yes	Yes	$104,000
	Budget 2	$400	$19,200	$3,000	$24,200	$3,200	Yes	$7,800	Yes	Yes	$104,000
	Budget 3	$4,000	$4,800	$3,000	$24,200	$64,000	Yes	$7,800	Yes	Yes	$104,000
	Budget 4	$7,200	$2,900	$1,100	$23,600	$115,200	Yes	$7,800	Yes	Yes	$104,000
	Budget 5	$1,200	$1,000	$5,200	$23,000	$169,600	Yes	$7,800	Yes	Yes	$104,000
Case 5	Budget 1	-	-	-	-	-	Yes	$7,800	Yes	Yes	$104,000
	Budget 2	$4,400	$3,800	$3,400	$22,400	$16,000	Yes	$7,800	Yes	Yes	$104,000
	Budget 3	$4,000	$4,800	$3,000	$24,200	$64,000	Yes	$7,800	Yes	Yes	$104,000
	Budget 4	$7,200	$2,900	$1,100	$23,600	$115,200	Yes	$7,800	Yes	Yes	$104,000
	Budget 5	$4,800	$4,800	$3,000	$24,200	$163,200	Yes	$7,800	Yes	Yes	$104,000

Table 4.33 Investment in the retail building

Deterministic Analysis		EEMs					EFMs			
		Infiltration Rate	Insulation Thickness	Emissivity of Roof	Solar Reduction Factor	Window SHGC	Temperature Control	Lighting Dimmer	Voltage Throttling	PV System
Case 1	Budget 1	-	-	-	-	-	-	$7,800	-	-
	Budget 2	$400	$19,200	$3,000	$24,200	$3,200	-	$7,800	-	-
	Budget 3	$4,000	$4,800	$3,000	$24,200	$64,000	-	$7,800	-	-
	Budget 4	$4,600	$9,600	$6,000	$24,200	$105,600	-	$7,800	-	-
	Budget 5	$4,800	$4,800	$3,000	$24,200	$163,200	-	$7,800	-	-
Case 2	Budget 1	-	-	-	-	-	Yes	$7,800	-	$104,000
	Budget 2	$600	-	$6,000	$24,200	$19,200	Yes	$7,800	-	$104,000
	Budget 3	$2,400	-	$3,000	$24,200	$70,400	Yes	$7,800	-	$104,000
	Budget 4	$2,000	$3,800	$3.400	$22,400	$118,400	Yes	$7,800	-	$104,000
	Budget 5	$4,800	$4,800	$3,000	$24,200	$163,200	Yes	$7,800	-	$104,000
Case 3	Budget 1	-	-	-	-	-	Yes	$7,800	Yes	$104,000
	Budget 2	$4,000	$3,800	$3.400	$22,400	$16,000	Yes	$7,800	Yes	$104,000
	Budget 3	$4,000	$4,800	$3,000	$24,200	$64,000	Yes	$7,800	Yes	$104,000
	Budget 4	$4,800	-	$5,600	$21,200	$118,400	Yes	$7,800	-	$104,000
	Budget 5	$4,800	$4,800	$3,000	$24,200	$163,200	Yes	$7,800	-	$104,000
Case 4	Budget 1	-	-	-	-	-	Yes	$7,800	Yes	$104,000
	Budget 2	$6,800	-	$3,000	$24,200	$16,000	Yes	$7,800	Yes	$104,000
	Budget 3	$4,000	$4,800	$3,000	$24,200	$64,000	Yes	$7,800	-	$104,000
	Budget 4	$7,200	$2,900	$1,100	$23,600	$115,200	Yes	$7,800	-	$104,000
	Budget 5	$4,800	$4,800	$3,000	$24,200	$163,200	Yes	$7,800	-	$104,000
Case 5	Budget 1	-	-	-	-	-	Yes	$7,800	Yes	$104,000
	Budget 2	$600	-	$6,000	$24,200	$19,200	Yes	$7,800	Yes	$104,000
	Budget 3	$4,000	$4,800	$3,000	$24,200	$64,000	Yes	$7,800	Yes	$104,000
	Budget 4	$7,200	$2,900	$1,100	$23,600	$115,200	Yes	$7,800	-	$104,000
	Budget 5	$4,800	$4,800	$3,000	$24,200	$163,200	Yes	$7,800	-	$104,000

PV is typically considered to be a cost-effective investment based on energy savings alone (Cengiz 2015). This changes at high capacity installations when there is a substantial amount of excess generation (more generation than the concurrent demand of the building). In that case, the economic viability depends strongly on the local feed-in rate or the cost of local storage. In our case buildings, the PV areas are rather limited and excess generation is not a big issue or does not occur at all. This means that PV in rate structures with sufficiently high electricity price is an automatic choice, even without counting the benefits of demand charge reduction as result of PV installation. All the cases under GP PLM-11 schedule do not select PV or only install a small number of the PV system, while in other utility rates, the optimal result suggests maximizing the size of PV system to gain a high NPV. This is because GP PLM-11 uses HUD to categorize the peak load frequency of the building. HUD is calculated as the monthly total energy consumption divided by the peak demand. Buildings with low HUD have a higher occurrence frequency of the peak demand and will be charged for a higher energy and demand charge rate. In our case buildings, installing a PV system reduces the monthly total energy consumption, therefore reducing the HUD. The cases presented in this chapter prove that installing a large PV system in the office and retail building will reduce the HUD below 200, at which point the building will be charged a much higher energy rate. Therefore, most optimal investment packages in GP PLM-11 do not suggest installing a PV system. This is an important insight as it is counter-intuitive to what most building operators would expect from PV installations. It turns out that this particular rate structure can, in fact, be a disincentive for PV installation.

Since utilities have been typically charging flat rates for electricity in the past, building owners only pay attention to EEMs that focused solely on reducing energy usage within a building while indifferent to the time in which energy usage was reduced. If the building transfer to a dynamic pricing rate, the monthly reduction through EEMs will get lower. Some utility companies provide TOU and non-TOU options for their clients. Electricity building owners should evaluate the energy flexibility feature in their buildings and decide which option could bring them the maximum bill savings.

Figure 4.93, Figure 4.94 and Figure 4.95 illustrate the daily load profile of three types of commercial buildings on August 17th, on which day the maximum demand in this year occurred. The rate structure 5 (SCE TOU-GS-3 option B) is selected. The blue curve represents the daily load profile of the baseline building. The orange curve represents the daily load profile of the building that has the maximum NPV in case 5 among all the five budget levels. The deterministic result implies that the optimal EEM and EFM package applied to the office and retail building can reduce the peak demand below 200 kW. In the hospital building, the peak demand is reduced close to 200 kW. It is important for building operators to choose an investment package that offers strong guarantees that the energy bill reduction will actually be achieved after the interventions are implemented. Such guarantee can not be given based on a deterministic analysis. A stochastic analysis that captures the influence of natural variabilities in parameters and usage scenarios and uncertainties in cost assumptions will need to be conducted for this. Chapter 5 will, therefore, focus on capturing variabilities and uncertainties and conducting an uncertainty analysis to show the uncertainty in the NPV. Chapter 6 will follow on to show how the optimal set of EEM and EFM will be influenced by these uncertainties, giving rise to a stochastic optimization.

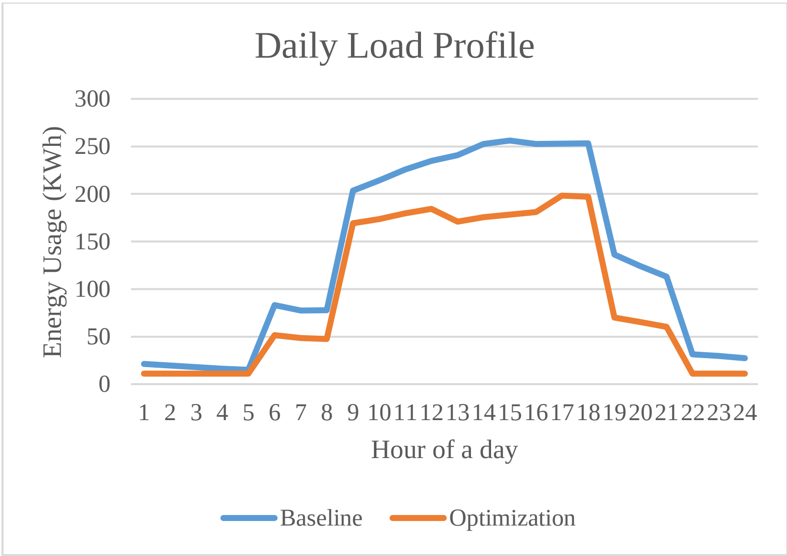


Figure 4.93 Office building daily load profile

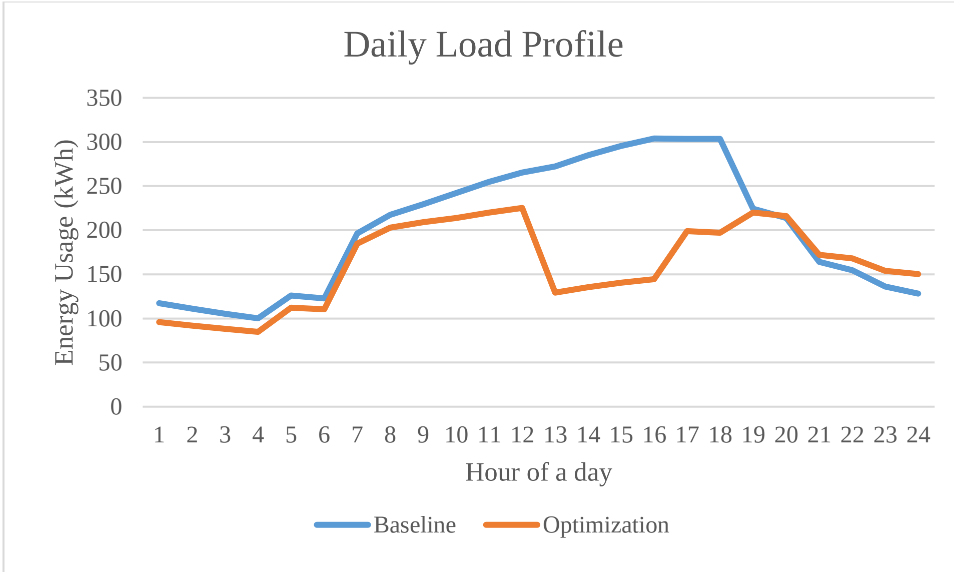


Figure 4.94 Hospital building daily load profile

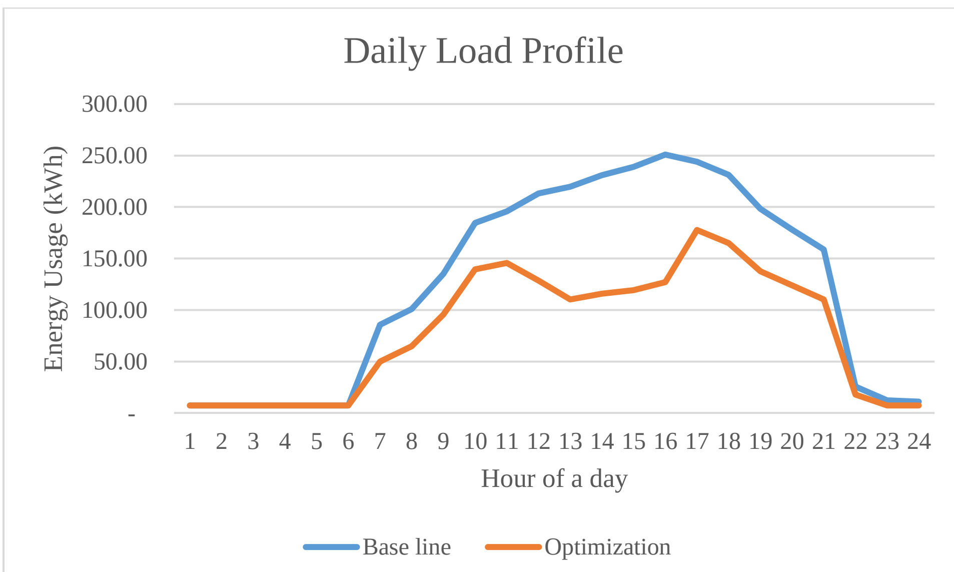


Figure 4.95 Retail building daily load profile

It is worth mentioning that, the EEM investment scale (budget levels) used in this study is dependent on the case building. For each building, the EEM budget levels scale will have to be determined specifically for that building. It will start with level 1 (the building as is, no budget) as is (level 1, no budget) and end with level 5 (all possible EEMs are applied at their highest achievement level, leading maximum budget). Budget levels 2, 3 and 4 are then defined as intermediate levels. It should be noted that there is a direct association between each EEM budget level and the EPC1 value (Energy Performance Coefficient for Energy Demand). Although this provides a good way to normalizing the budget levels, the same is not true for the peak load. This realization leads to the conclusion that the results in this chapter are case specific, that as yet cannot be translated to generic conclusions. Scaling to smaller or larger size peer buildings cannot be done due to the fact that demand charges are too much dependent on the size of the building. Nevertheless, the results discussed in the study reveal the complexity of the optimization problem and projects a possible trend of demand charge reduction potential of EFMs in buildings with different energy efficiency levels. As long as generic conclusions are hard to develop, a good alternative is a tool that can be used by building operators to determine the optimal EEM+EFM package for their specific building. Such a tool has been developed as a major deliverable of this thesis. The DIY tool is directed towards commercial building owners to allow them to determine the optimal investment strategy for their specific buildings. It will be described in Chapter 7.

CHAPTER 5 UNCERTAINTY QUANTIFICATION AND ANALYSIS

Models are ideal representations of the real physical world with different levels of abstraction and fidelity. Before utilizing a model to make predictions or decisions, it is important for the user to obtain a deep understanding of the accuracy and reliability of the model. The traditional method to evaluate the correctness of a model is to compare the outcomes of the model with real measurements and repeat that experiment under many different scenarios. However, in the building discipline, each building model only has one realization at a time. As a result, we forfeit the objective to construct absolutely correct models. Instead, we estimate the uncertainty in our model outcomes based on estimating the uncertainty or variability of the model parameters. We can judge these uncertainties fairly well based on previous research (De Wit 2001, Macdonald 2002, Sun et al. 2014). Based on these investigations, we use a generic uncertainty analysis to help us understand the variability of our model outcomes and estimate the level of confidence in the predicted result. given the range of irreducible uncertainty in our model parameters and (in the extreme case) in the model itself. The latter is called model form uncertainty (Sun et al. 2014, Sun et al. 2015) which is out of the scope of this study and ignored. Instead, we will show in Chapter 7 that our model is accurate enough for our comparative studies thus rendering model form uncertainty is less relevant. Our focus in this chapter is therefore on the most relevant model parameters, i.e. those that can add significant uncertainty to peak power and consumption predictions. Conducting an uncertainty analysis can also help us gain insights into identifying the most influential sources of uncertainty.

Walker et al. (2003) defined uncertainty as “being any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system.” Indeed, no physical-mathematical model can be trusted with perfect certainty. Solely relying on the prediction from a low-fidelity deterministic model with high uncertainty may lead to the wrong choices and thus carry a substantial investment risk. In order to make rational investment decisions, it is necessary to conduct an uncertainty analysis, which quantifies the risk associated with the decision analysis model. De Wit and Augenbroe (2002) integrated UQ with risk analysis in a decision-making context. This study concluded that if the decision maker was informed about uncertainties in the prediction, they could have chosen different design alternatives. Heo et al. (2012) extended the application of UQ to support risk-conscious decision making in building design and retrofit when decisions are driven by financial return on the investment.

The prediction of energy consumption is usually based on the aggregated electricity usage over a certain time period (typically one month or one year), which is insensitive to the spikes of the usage in that period. However, the estimation of peak demand is based on an averaged electricity usage over a short time period (typically 15 or 30 minutes). The steepness in the load profile will be reflected in the peak demand. Therefore, peak demand is difficult to predict due to its highly dynamic nature, and, in general, it is expected to be more sensitive to the variability of model parameters. The analysis in this chapter replaces the deterministic simulation of peak demand and total energy in the building with a probabilistic prediction. Hence, the optimization, as a comparative analysis over all options in the parameter space, needs also to work with probabilistic distributions, which turns the deterministic optimization into a stochastic optimization problem. Before we get to the stochastic optimization in Chapter 6, we will describe in this chapter the impact of uncertainties on the optimal solutions that were found in Chapter 4. We start from a preliminary analysis of uncertainties that reside in relevant model parameters. Then, we propagate all of these identified uncertainties through the model using a Monte Carlo engine that runs repeatedly with different values sampled from the parameter uncertainty distributions. In the last step, we will combine outcomes from all these samples and construct a distribution for the variable of interest.

For the study of peak loads, we have focused on uncertainty in a typical set of parameters that represent physical parameters and usage and occupancy scenarios that cannot be precisely known. These are the typical building energy model parameters. They have the main influence on the benefit side of NPV as they impact the prediction of peak loads and energy consumption and thereby the prediction of savings. In addition, there are uncertainties in models that quantify the costs (or damages) of proposed measures such as in the monetary cost of technologies, future changes in the utility's rate policy, performance deterioration of certain technologies and the others. It is obvious that cost side uncertainties have a significant influence in the NPV valuation of an EEM+EFM selection, and thus need to be considered when making an investment decision. The quantification of those uncertainties in physical properties and usage scenarios is based on the UQ repository developed in previous work in the EFRI-SEED project. The UQ repository stores the probabilistic distribution of the building energy model parameters summarized from previous work (De Wit 2001, Macdonald 2002, Sun et al. 2014). For the three cost side uncertainties, no data exists in the repository. In the next sections, we will quantify three sources of uncertainty: (1) the loss of productivity at different temperature levels, (2) cost of EEM related to products and labor fees, and (3) future change of demand charge rates. Each could be added into the UQ repository in the future. The last section of this chapter will then illustrate how the resulting uncertainty leads to a variability in predicted peak loads, energy consumption, and NPV.

5.1 Uncertainty Quantification

As explained above, we focus on quantifying uncertainty in the loss of productivity, cost of products, and future change of demand charge rate.

The method of implementing parameter and operation scenario uncertainties in EPC will be introduced in section 5.2. We will discuss how quantified expressions of uncertainties is implemented in the current hourly EPC calculator and its add-on NPV calculation. The UA and SA are conducted with the resulting model. This serves a deeper inspection of the results obtained in the previous chapter in order to evaluate the potential impact of different parameters on the optimal investment solutions that were found.

5.1.1 Uncertainty in Productivity Loss

A comfortable or neutral indoor temperature represents the range of temperatures at which the air feels neither hot nor cold under the normal clothing level (0.5 Clo). It is an essential characteristic that describes the indoor environment. Evidence in the literature has shown that room temperature has a considerable influence on the physiological and subjective human responses, such as thermal comfort, sense of indoor air quality and productivity of work (Willem 2006, Lan et al. 2011).

The average office worker's salary is approximately double the cost of the building operation and maintenance cost per worker (Djukanovic 2002). A 1% change in the productivity of workers has a considerable impact on the bottom line of the organization. In this study, a prominent EFM introduced in the previous chapters increases the temperature setpoint during peak load periods. This leads to temperature increase and related loss of productivity for a limited time. Using an adequate model to predict productivity loss is crucial in order to avoid that this EFM is over or under utilized, due to the big impact of productivity loss on the NPV of the set of proposed measures. Seppanen et al. (2003) claimed that the upper boundary of the thermal neutrality is 25℃. Above this point, there will be a penalty in the form of a productivity loss will be added to formulas of economic analysis. However, this boundary value is very vague and hard to pinpoint in a specific situation and could, therefore, lead to an over- or underestimation of the productivity loss. The author cited the conclusion from Federspiel et al. (2002) that temperature variations between 21.5 and 24.75 ℃ did not appear to significantly affect a worker's productivity. The author further referred to Witterseh (2001) to support the proposed no-effect range. The 21 to 25℃ temperature range is also close to the range of temperatures considered comfortable in some thermal comfort standards (ASHRAE 2004). However, results from these studies were performed in field laboratories with pre-conditioned, biased sources. The thermal neutrality ranges concluded from these studies are merely approximations without validation from real office conditions.

Literature that focuses on the relationship between indoor temperature and productivity loss is not scarce. Berglund et al. (1990) collected the performance data of wireless telegraph operator in different interior thermal conditions. This paper first utilized the physiological thermal model that relates the productivity to the effective temperature and then derived the relationship between productivity loss and indoor temperature from this model. Wyon (1996) inspected the impact of room temperature on the productivity loss based on the measurement data of workers' thinking and typing performance in an office space. The experiment revealed that for the thinking task, productivity started to decrease at 21℃ and reduced by 30% at 27℃; for the typing task, productivity started to decrease at 21℃ and reduced by 30% at 24℃. He equally weighted each task and summarized the relationship of the decrement of the performance of office works as a function of the actual temperature. Niemelä et al. (2001) claimed a decrement of 1.8% per ℃ in the productivity of workers in a call center when the temperature was above the range of thermal neutrality, which is roughly estimated to range from 21 to 25℃. In a follow-up experiment performed in the same call center, Niemelä et al. (2002) reported a decrement of 2.4% per ℃ in the productivity. Federspiel et al. (2002) measured the productivity of workers in a call center by their speed of completing a talk task. The study claimed no significant relationship between the productivity and the indoor temperature within the range from 21 to 25.4℃, but a 16% loss in the productivity as the temperature reaches 26℃. Seppänen et al. (2003) proposed a relationship between a worker's performance and the temperature. It showed a 2% decrease in the performance by one degree celsius increase of the temperature in the range of 25 to 32℃ and no effect on worker's performance in the temperature range of 21 to 25℃. Seppänen et al. (2004) assembled information from the literature on how the temperature affects productivity and how to incorporate the effect of productivity loss in the cost-benefit analysis in building design and operation investment. Kosonen (2004) assessed the productivity loss in buildings using the PMV index and derived the relationship between productivity decrement and indoor temperature. Seppänen et al. (2006) reviewed twenty-four relevant studies on productivity loss and proposed a cubic formula to describe the relationship between indoor temperature and worker's productivity. Lan et al. (2011) derived the relationship between productive decrement and indoor temperature from the estimation of room air temperature from thermal sensation votes.

The experiment results collected from these studies are limited to laboratory conditions where they examine effects of temperature on the performance of some mental and other tasks simulating office work. The fitness of applying the experiment data to performance in actual office environments is not clear. If we have no further data and have no evidence to prioritize one study over the other, we should consider all cited empirical studies as equally likely in estimating the actual productivity loss over indoor temperature. Thus, the impact of indoor temperature on productivity loss can be quantified by reviewing the models and values reported in published literature and standards and approximating the functions in the literature with linear functions of the following form:

$$P = aT + b \tag{5.1}$$

Table 5.1 summarizes the relationship between indoor temperature and productivity loss developed in the literature since the 1960's.

Table 5.1 Relationship between room temperature and productivity loss in the literature

Models	Environment of the study	References
$P = 0.004T - 0.106$	Classroom	(Pepler 1968)
$P = 0.0094T - 0.2259$	Apparel factory	(Link & Pepler 1970)
$P = 0.0067T - 0.1533$	Classroom	(Johansson 1975)
$P = 0.025T - 0.65$	Laboratory measurement	(Berglund 1990)
P = 0.05T - 1.0179	Laboratory measurement	(Wyon 1996)
P = 0.018T - 0.3942	Field measurement	(Niemela 2001)
P = 0.024T - 0.6	Field measurement	(Niemela 2002)
P = 0.2667T - 6.7733	Field measurement	(Federspiel 2002)
P = 0.02T - 0.5	Model approximation	(Steppanen 2003)
P = 0.0437T - 0.8498	Theoretical analysis	(Kosonen 2004)
P = 0.0518T - 1.1232	Theoretical analysis	(Kosonen 2004)
P = 0.0614T - 1.4529	Theoretical analysis	(Kosonen 2004)
P = 0.0146T - 0.3503	Model approximation	(Steppanen 2006)
P = 0.011T - 0.242	Field measurement	(Lan 2011)
T - Thermostat setting	P - Productivity loss	

The next step is to create a uniform model in which a and b are considered uncertain. In order to estimate the distribution of a and b, we adopt the bivariate kernel density estimator to evaluate the density of the two coefficients. The mathematical function of the bivariate kernel density estimator is:

$$\hat{f}_H = \frac{1}{n}\sum_{i=1}^{n} K_H(x - x_i) \tag{5.2}$$

Where $x_i = (a_i, b_i)^T, i = 1,2, \dots, n$ are the indices of observation paries, K is the kernal function, and H is the bandwidth matrix, and K_H is given by

$$K_H(\mathrm{x}) = |\mathrm{H}|^{-\frac{1}{2}} K(|\mathrm{H}|^{-\frac{1}{2}} x) \tag{5.3}$$

The bandwidth matrix H is determined by optimization. The kernel function is a bivariate Gaussian distribution. To visualize the uncertainty in the calculation of the productivity loss, Figure 5.1 shows the box plot of the values of productivity loss at different indoor temperature. The x-axis represents the difference between the actual temperature and the "neutral" setpoint temperature. In this thesis, we adopt a neutral temperature 24 ℃ in the office and retail building case, and 21℃ in the hospital case. The median value of the productivity loss increases moderately from 6% to 11% when the indoor temperature is increased from 24 ℃ to 30 ℃. However, the distribution of the productivity loss has a long tail towards higher values and has a wide base. Conclusions that counter common sense can be drawn from the long tail such as people would lose 30% of their productivity at indoor temperatures of 25℃. This result would indicate that changing the thermostat setting could incur a significant change in productivity. Most variability in the prediction of productivity loss comes from the long tail, which could be the result of training our model with several over conservative models reported in the literature. If we only focus on the median value of the productivity loss percentage, we could find that people are indifferent to the temperature change within a certain range. If we integrate the productivity loss uncertainty in our comprehensive uncertainty analysis model, it will obviously add a long tail of negative impact on the NPV, which creates a long negative tail for the NPV distribution. Due to its heavy impact, we split the analysis in section 5.2 into two parts. In the first part, we inspect the change of NPV with different productivity loss uncertainty included. Then, we exclude it from the uncertainty analysis.

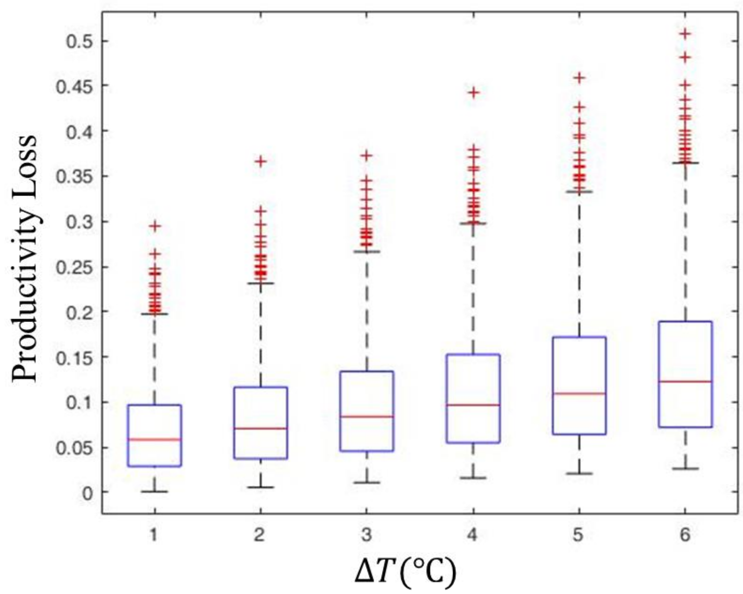


Figure 5.1 Box plot of productivity loss as function of indoor temperature increase above neutral temperature

5.1.2 Uncertainty in Product Cost

The cost estimation of each energy efficient measure plays an important role in the optimization process, as it may eventually change the decision about which measures will be applied. The methodology used for estimating cost is kept very simple. The common inputs of the calculation include but are not limited to the cost of the material, labor, delivery, preparation of worksite, testing, and if any permit or testing is required by the local code regulations. Those inputs themselves, however, are not easy to be estimated precisely. For instance, one major component of cost, the labor fee, may vary based on the project location, selection of the contractor, and whether extra work is required to remove the existing installations. What's more, cost risks, as another measurable part of the cost uncertainty, can also add a positive or negative deviation to the final cost. Risks of project cost can be classified into the following six categories: quality risks (e.g. lack of quality control and tests), personnel risks (e.g. lack of skills), cost risks (e.g. planning changes, complicated project conditions), set date/deadlines risks (e.g. the project end is delayed), risks of strategic decisions(e.g. fail to recognize opportunities), and external risks (e.g. political changes). The quantification of risks and other cost uncertainties, which requires assessing individual uncertainties with their correlated effects, is a complicated process and requires professional judgment based on individual project condition. Therefore, our analysis will not go that far, and a rule of thumb will be used. The common cost of the measures is listed in Table 4.16. To all the costs, a 10% variance will be added. The simplicity of this approach is warranted as a first step to understanding the relative influence of different sources of uncertainty.

5.1.3 Uncertainty in the Future Demand Charge Rate

Electricity rates reflect the cost to build, maintain, and operate power plants and the transmission and distribution system. Utility rates have a dynamic nature. Therefore, we have to accept that future demand charge rates are uncertain. One working assumption could be that they are based on or even linearly correlated with the predicted change of peak demand in the power grid.

Predictions of peak load in the grid have been made by some utility companies. Xcel energy projects an annual growth rate of 0.4 percent on the peak load in its service territory during the 2016 to 2030 planning period (Xcel 2016). ERCOT (2017) claims that there will be a 1-2% increase in the peak demand in the power grid from 2017 to 2025 in Texas. All these future projections made by the utility companies indicate an upward trend of the peak load in the future grid even with a growing DER involvement. The DER share is expected to grow as costs go down

(DERs only cost 50% of what they did three years ago) and DOE keeps investing in efforts that discover innovative technologies which could further drive down the cost of PV (DOE 2014). It is highly possible that the DERs take a substantial share of the electricity market in the coming years. International energy outlook (2016) predicts that world net electricity generation would increase 69% by 2040. It is possible that the future growth of power demand exceeds the growth of distributed generation. However, the utilities are holding a conservative attitude towards the future market share of DERs when making the prediction of peak load growth in the power grid. In order to take a neutral attitude, we assume that the average trend is 0 (no change in demand charge rates) with a +/- 2% range. It is applied to each specific utility rate case as a simple multiplication factor on the calculated demand charge. This study simplifies this process even further by assuming a uniform distribution of this multiplication factor between 0.98 and 1.02 and using the same value for the whole 20 year time horizon in the NPV calculation.

It should be kept in mind that the regular uncertainties in relevant building energy model parameters are considered in conjunction with above "special" sources of uncertainty. Among the energy model parameters, we treat the operational scenario, U-value of the walls, U-value of the windows, infiltration rate as key uncertain parameters. Assuming there is only limited knowledge about how will the building be operated in reality, this study assumes the scenario uncertainty is 20%, while the other model parameter uncertainty is 10%.

5.2 Uncertainty Analysis

In this section, we propagate uncertainties in energy model parameters, scenario parameters, productivity loss formula, product cost and future demand charge rate that are listed in Table 5.2. We do this for the optimal EEM+EFM cases determined in Chapter 4, i.e. the building with EEM+EFM that has the maximum NPV. Below, the results are shown for the optimal EEM+EFM investment (maximum NPV) cases found in Chapter 4 for office, hospital and retail building for rate case 5. For each case, the variability in peak load distribution (on the peak load day), NPV distribution with SA is presented.

Table 5.2 List of uncertainty parameters

	Uncertainty Parameter	Range
Energy Model Parameter	U-value of Wall	-10% ~ +10%
	U-value of Window	-10% ~ +10%
	Infiltration Rate	-10% ~ +10%
Scenario Parameters	Occupancy Density	-20% ~ +20%
	Appliance Density	-20% ~ +20%
Cost Factors	Productivity Loss	Bivariate Kernel Density
	Product Cost	-10% ~ +10%
	Future Demand Charge Rate	-2% ~ +2%

5.2.1 Office Building Uncertainty Propagation

In this subsection, we analyze the uncertainties in NPV and load profile the office building case 5. In case 5, it was found that the thermostat adjustment is not part of the optimal EEM+EFM package, which implies that the uncertainty in productivity loss is irrelevant as the setpoint adjustment is not part of the selected EFM mix. (We assume no productivity loss if the thermostat adjustment option is not selected, as other temperature adjustments, such as may happen with voltage reduction (if it is among the selected EFM) will not lead to higher temperature). Figure 5.2 shows the results of NPV at different budget levels with the optimal EEM + EFM. The result reveals that budget level 5, achieving the maximum NPV in the deterministic analysis, still shows the highest median value of NPV. However, it is not necessarily the optimal package anymore considering that the outliers at the lower bound of NPV range incorporate a significant downside risk for the chosen EEM+EFM mix. It may in such a case well be possible that a better optimum occurs at another budget level. This will be explored in the next Chapter.

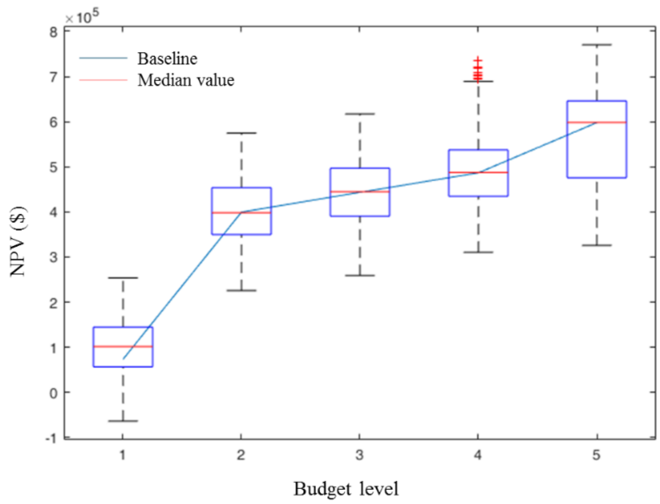


Figure 5.2 NPV results of combined EEM and EFM under uncertainty (refer to Figure 4.31 for reference)

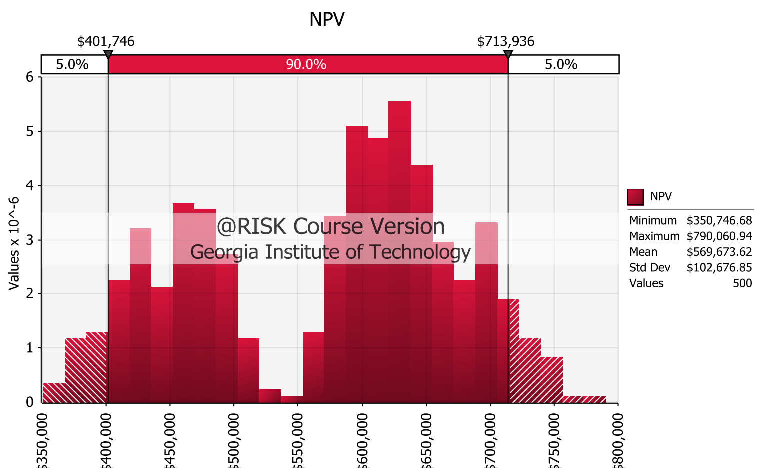


Figure 5.3 Distribution of the NPV at budget level 5

The distribution of the NPV at the optimal investment in the deterministic analysis (occurring at budget level 5) is shown in Figure 5.3. It is notable that the distribution of NPV is a bimodal distribution. This is caused by the switching between rate schedule TOU-GS-3 and TOU-GS-2 that occurs if certain specific conditions are satisfied. As introduced in Chapter 4, if an SCE customer in the rate schedule of TOU-GS-3 reduces the peak demand below 200 kW, he will be switched to TOU-GS-2 rate, which has a higher energy rate but a much lower demand charge rate.

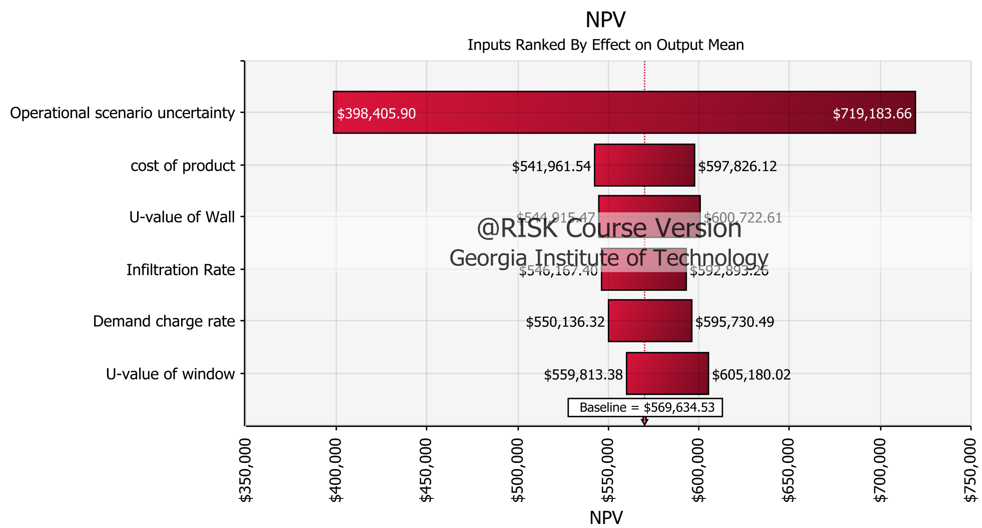


Figure 5.4 SA based ranking of parameters

Figure 5.4 ranks the significance of each parameter in the resulting NPV distribution based on the change in the output mean and the regression coefficient. The top three factors that have the most significant impact on the NPV are the operational scenario, the cost of the product, and U-value of the wall.

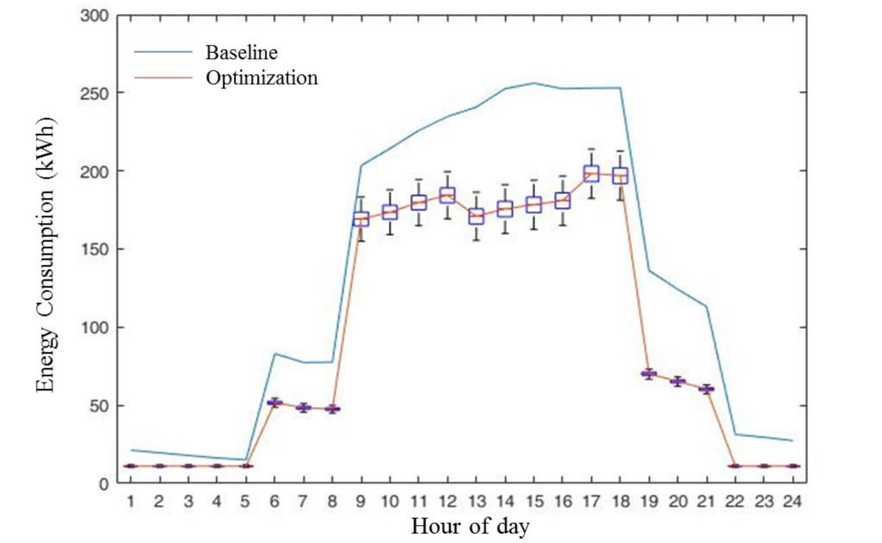


Figure 5.5 Office building peak day load profile (use Figure 4.93 as reference)

Comparing Figure 5.5 to Figure 4.93 (indicated here as the red line) confirms that the peak load will probably still occur at 17:00, although there is a small probability that the load at hour 18 is higher. Another interesting result that can be derived is that optimization package can reduce the peak power below 200 kW with 65% confidence (200 kW occurs at the 65 percentile).

5.2.2 Hospital Building Uncertainty Propagation

In this subsection, we analyze the uncertainties in NPV and load profile the hospital building case 5. Figure 5.6 shows the results of NPV at different budget levels with the optimal EEM + EFM. The result reveals that budget level 5, achieving the maximum NPV in the deterministic analysis, still shows the highest median value of NPV. However, it is not necessarily the optimal investment. In fact, the EEM+EFM package at budget levels 2, 3, and 4 can give NPV close to each other.

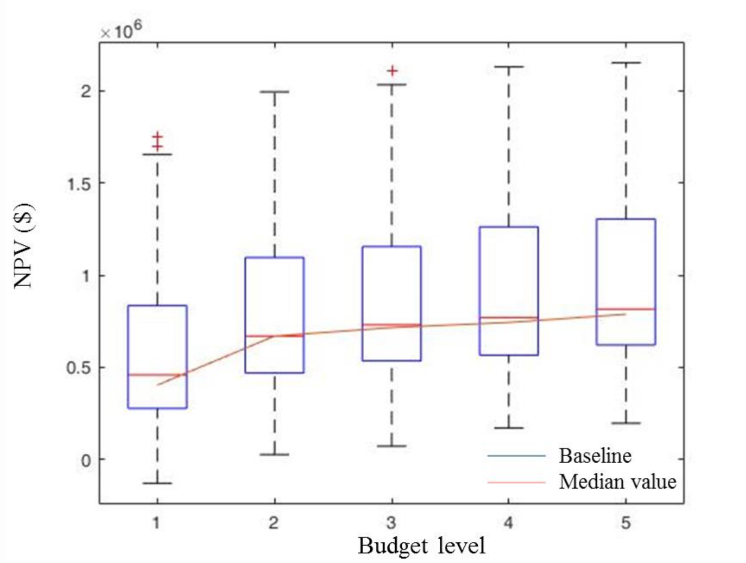


Figure 5.6 NPV results of combined EEM and EFM with uncertainty (refer to Figure 4.62 for reference)

The distribution of the NPV at the optimal investment in the deterministic analysis (budget level 5) is shown in Figure 5.7.

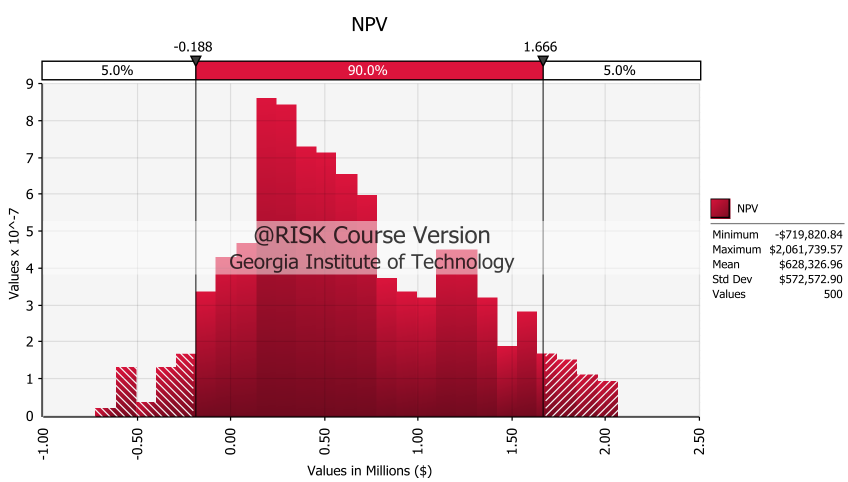


Figure 5.7 Distribution of the NPV at budget level 5

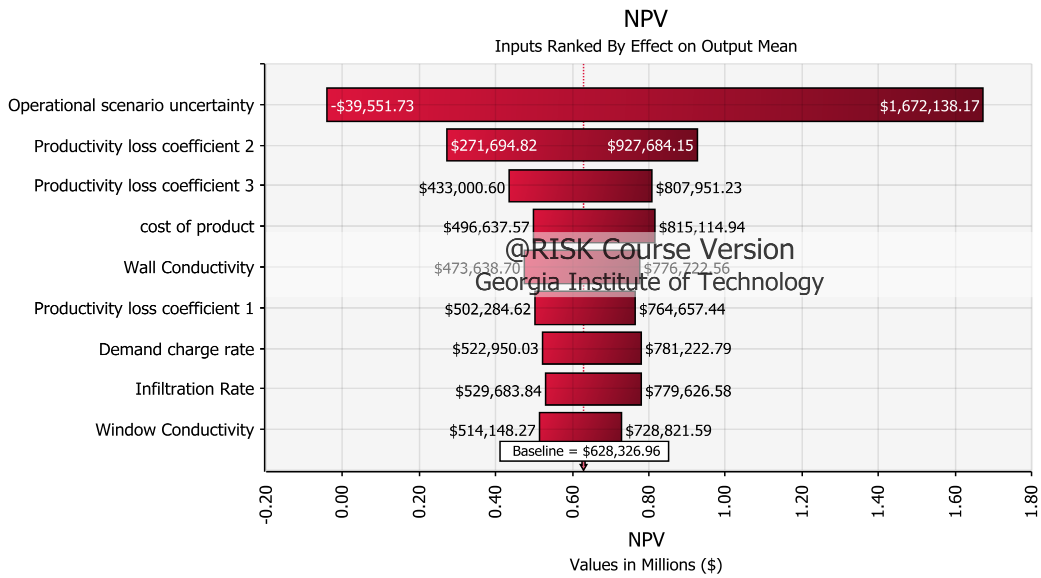


Figure 5.8 SA based ranking of parameters

Figure 5.8 ranks the significance of each parameter in the resulting NPV distribution based on the change in the output mean and the regression coefficient. The top three factors that have the most significant impact on the NPV are the operational scenario, productivity loss coefficient, and cost of products.

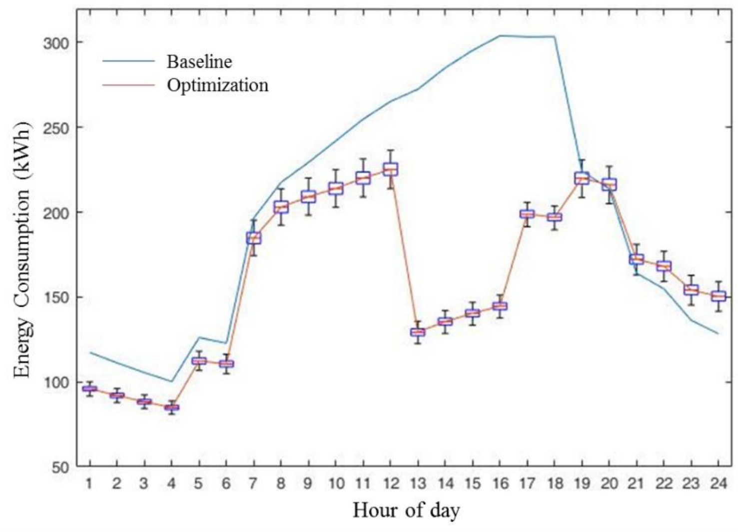


Figure 5.9 Hospital building peak day load profile (use Figure 4.94 as reference)

Comparing Figure 5.9 to Figure 4.94 confirms that the peak load in the optimization case will probably still occur at 12 noon, although there is a small probability that the load at hour 17 is higher. Another interesting result that can be derived is that optimization package can reduce the peak power below 200 kW with 30% (200 kW occurs at the 30 percentile).

5.2.3 Retail Building Uncertainty Propagation

In this subsection, we analyze the uncertainties in NPV and load profile for the hospital building at rate case 5. The distribution of the NPV at the optimal investment in the deterministic analysis (budget level 5) is shown in Figure 5.10. The long tail of negative values of NPV is caused by the productivity loss uncertainty, which is confirmed in Figure 5.11, the result of which shows that the productivity loss ranks the top factor that has a significant impact on NPV. Due to its heavy impact in this case which includes DR among the optimal EFM, we split the analysis into two parts. The analysis in the following part will exclude the productivity loss uncertainty. We will use the same productivity loss formula as in the deterministic analysis.

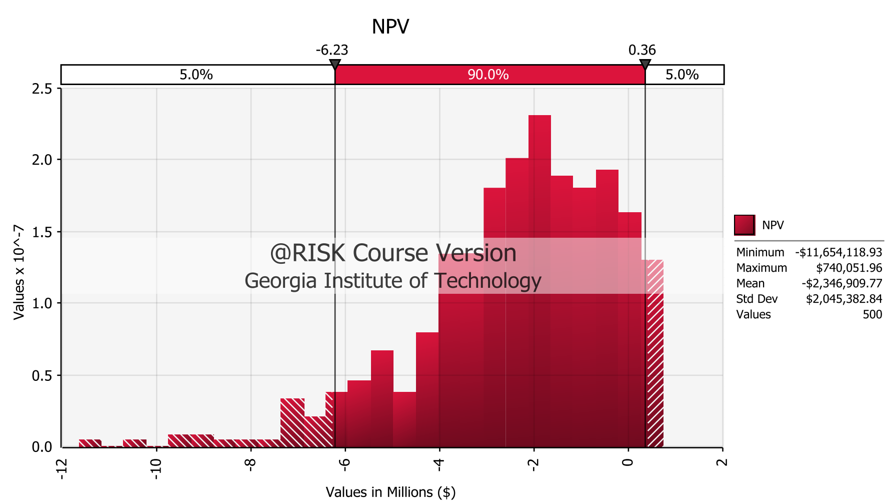


Figure 5.10 Distribution of the NPV at budget level 5

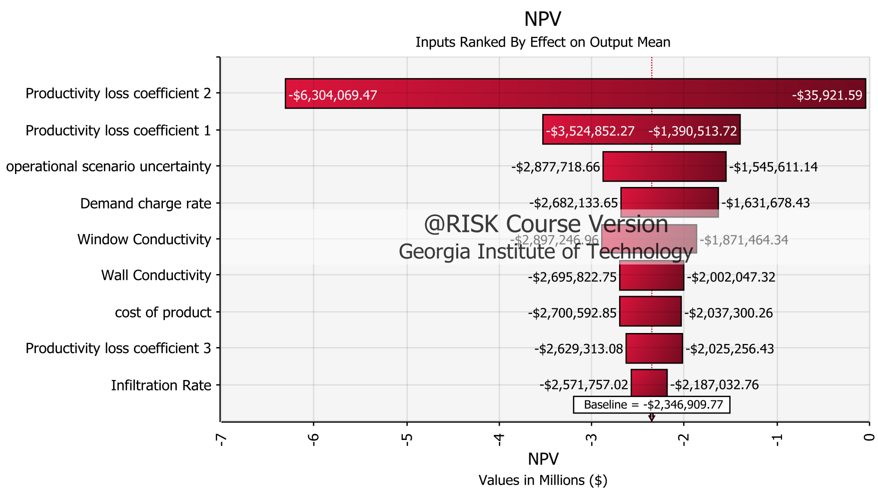


Figure 5.11 SA based ranking of parameters

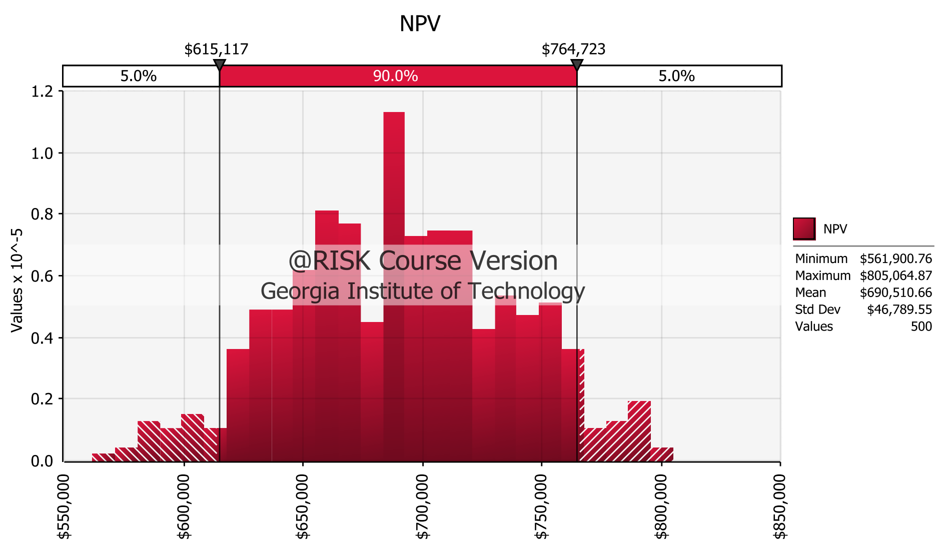


Figure 5.12 Distribution of the NPV

The distribution of the NPV at the optimal investment in the deterministic analysis (budget level 5) is shown in Figure 5.12. Excluding the uncertainty of the productivity loss, we will see a much shorter tail on the lower values of the NPV distribution.

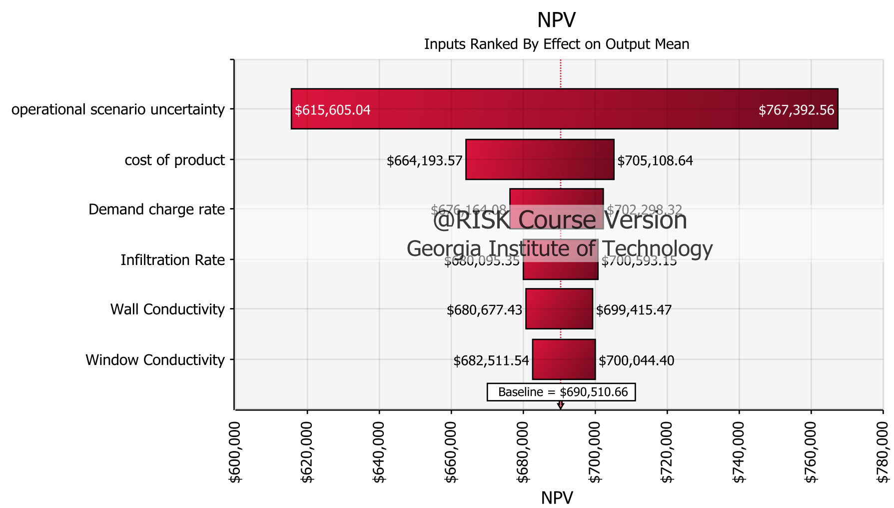


Figure 5.13 SA based ranking of parameters

Figure 5.13 ranks the significance of each parameter in the resulting NPV distribution based on the change in the output mean and the regression coefficient. The top three factors that have the most significant impact on the NPV are the operational scenario, the cost of the product, and demand charge rate.

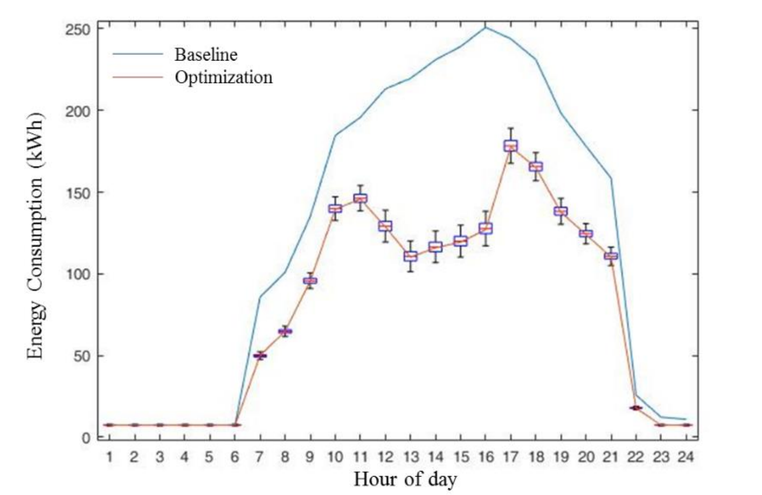


Figure 5.14 Office building peak day load profile (use Figure 4.92 as reference)

Comparing Figure 5.14 to Figure 4.95 confirms that the peak load in the optimization case will probably still occur at hour 18. The results reveal that the optimization package can reduce the peak power below 200 kW with 100% confidence.

5.2.4 Summary of the Uncertainty Analysis

The first section of this chapter quantifies the uncertainty in productivity loss through bivariate kernel density function. The next section analyzes the risk in the NPV and daily load profile for the three types building under SCE TOU-GS-3 option B rate with the uncertainty in productivity loss, product cost, future demand charge rate, physical parameters, and usage scenarios.

This chapter addressed the importance of recognition of uncertainties in predicting the effect of EENM and EFM in energy cost and demand charge reductions. The analysis points to some severe risk factors in the NPV that will actually be realized. It will, therefore, be necessary to re-examine the deterministic optimizations from Chapter 4 and recast them as stochastic optimization problems, as this will allow to specifically manage the downside risks of any suggested intervention package. Chapter 6 will carry out the stochastic optimization and illustrate how different optimization criterion leads to distinct investment decisions.

CHAPTER 6 FINDING THE OPTIMAL SET OF MEASURES UNDER UNCERTAINTY

Most real world problems unavoidably include some parameters that cannot be fully known, i.e. they are to some extent uncertain. Investment decisions are always formulated as optimization problems in the presence of uncertainty. Therefore, decision makers are often required to solve optimization problems with uncertain parameters and hence non-deterministic outcomes of the objective function. Dantzig (1955) started the first attempt of modeling by assuming that part of the input can be modeled as probability distributions that reflect imperfect knowledge. Whereas deterministic optimization problems are formulated with known parameters, stochastic optimization problems are formulated with parameters that are not precisely known and can only be assumed to lie in a range where only the bounds of this range can be known with sufficient level of confidence. The problem is then formulated as the minimization or maximization of a cost or profit function in the presence of uncertainties that need to be reflected in the optimization process (Gentle et al. 2012). This can, in short, be referred to as stochastic optimization. One of the main characteristics of such optimization is that it is no longer sensible to look only for the solution that optimizes the expected mean value of the cost function. Indeed, solutions that deliver the optimum in that sense may for diverse reasons be less desired than other solutions that come close enough to the lowest expected mean of the cost function, but at the same time deliver a desired characteristic of the cost probability distribution, typically represented by one or more risk preferences of the decision maker. A typical example is the shortest travel time between two points as shortly explained below. Although one of the roads is on average very open and thus fast, there are a few days that it is very congested. On those few days, the route will lead to long delays. There is an alternative route that is slower but never congested. Taking the first route every day would (on average) lead to the optimal expected mean of the travel time. However, based on the risk acceptance of a traveler, she may decide to never use the first (on average) optimal route and choose the alternative (on average slower) route, just to make sure that she is never more than 30 minutes late. This example is relevant for many investment decisions where there is always a risk that multiple adverse situations coincide leading to undesired results. Quantifying that risk is essential to the analysis.

The previous chapters formulate the decision making problem (Chapter 4), followed by an uncertainty analysis of the optimum configurations, based on quantified uncertainty in the input parameters (Chapter 5) of the decision analysis model. This chapter will carry out a stochastic optimization with specified user preferences in order to make a rational investment decision in the recognition of all uncertainties. The study in this chapter will illustrate how different optimization criteria can lead to different investment decisions. We will show how the optimal investment choice is affected by the uncertainty in the cost of the measures, for instance how small changes in the productivity loss model impact the optimal mix of measures. In the next section, we will first introduce the concept of deriving useful risk criteria for stochastic optimization, The concept of robust design will be elaborated for that purpose.

6.1 Robust Design Criterion

The goal of the robust design is usually to determine the optimum set of parameters that will minimize the variability of the response about some ideal target value. Rather than employing axiomatic utility theory, this thesis adopts a heuristic “robustness” criterion. Defining such a criterion for a given decision maker that is appropriate in the given optimization context is a major intellectual challenge that does not fit in the scope of this thesis. In lieu, this section introduces a number of plausible risk preference profiles, and section 6.2.1 will show the outcomes for these heuristically determined profiles.

The problem of maximizing the NPV function can be formally represented as finding the set:

$$\Theta^* = \arg\max_{\theta\in\Theta} NPV(\boldsymbol{\theta}, \boldsymbol{\xi}) = \{\boldsymbol{\theta}^* \in \Theta : NPV(\boldsymbol{\theta}^*, \xi) \leq NPV(\boldsymbol{\theta}, \xi)\} \qquad (6.1)$$

Where $\boldsymbol{\theta}^*$ is the solution set of measures (each characterized by a set of parameters) that maximizes the value of the *NPV* function, $\boldsymbol{\theta}$ is the *p*-dimensional vector of parameters that are being adjusted, $\boldsymbol{\xi}$ is the *p*-dimensional vector of non-adjustable parameters in the *NPV* function. The "$\arg\max_{\theta\in\Theta}$" statement in (6.1) should be read as $\Theta^*$is the set of values $\boldsymbol{\theta} = \boldsymbol{\theta}^*$ that maximize $NPV(\boldsymbol{\theta}, \boldsymbol{\xi})$ subject to $\boldsymbol{\theta}^*$ satisfying the constraints represented in the set Θ. The elements $\boldsymbol{\theta}^* \in \Theta^* \subseteq \Theta$ are equivalent solutions since they have the identical outcomes of the *NPV* function. The solution set Θ^* in (6.1) could be a unique point, a set of countable or uncountable points.

In the context of this study, we select three stochastic criteria of the plausible risk preference profiles.

(1) $\boldsymbol{\theta}^* = \arg\max_{\theta\in\Theta} E\{NPV(\boldsymbol{\theta}, \boldsymbol{\xi})\}$

The first criterion is to find the optimal set that maximizes the expected mean of the objective function. With this stochastic criterion, the optimization algorithm will search for the set of values

$\boldsymbol{\theta} = \boldsymbol{\theta}^*$ that maximize the expected mean of $NPV(\boldsymbol{\theta}, \boldsymbol{\xi})$ subject to $\boldsymbol{\theta}^*$ satisfying the constraints represented in the set Θ.

$$(2)\ \boldsymbol{\theta}^* = \arg\max_{\theta \in \Theta} E\{NPV(\boldsymbol{\theta}, \boldsymbol{\xi})\} \,\&\, \sigma\{NPV(\boldsymbol{\theta}, \boldsymbol{\xi})\} \leq V_{limit}$$

The second criterion is to find the optimal set that maximizes the expected mean of the objective function and guarantee that the standard deviation is not higher than a prescribed value. With this stochastic criterion, the optimization algorithm will search for the set of values $\boldsymbol{\theta} = \boldsymbol{\theta}^*$ that maximizes $E\{NPV(\boldsymbol{\theta}, \boldsymbol{\xi})\}$ and guarantee that the standard deviation of $NPV(\boldsymbol{\theta}, \boldsymbol{\xi})$ is not higher than V_{limit} subject to $\boldsymbol{\theta}^*$ satisfying the constraints represented in the set Θ. In many financial optimization contexts, this criterion is less appropriate as it expresses a symmetrical constraint on the distribution. In reality the constraint is not symmetrical as a downside risk is obviously more relevant that the upside "risk". The following crietrion is therefore more appropriate for our purposes.

$$(3)\ \boldsymbol{\theta}^* = \arg\max_{\theta \in \Theta} \mathrm{E}\{NPV(\boldsymbol{\theta}, \boldsymbol{\xi})\} \,\&\, Prob\{NPV(\boldsymbol{\theta}, \boldsymbol{\xi}) \geq V_{limit}\} > Prob_{limit}$$

The third criterion is to find the optimal set that maximizes the *NPV* and guarantees the probability of the risk measure (typically the risk that the NPV is less than a limit value) not exceeding an acceptable limit. In the formula, this is expressed as requiring the probability of the NPV above a certain limit value to be guaranteed with a level of certainty. With this stochastic criterion, the optimization algorithm will search for the set of values $\boldsymbol{\theta} = \boldsymbol{\theta}^*$ that maximize the $NPV(\boldsymbol{\theta}, \boldsymbol{\xi})$ and ensure that $Prob\{NPV(\boldsymbol{\theta}, \boldsymbol{\xi}) \geq V_{limit}\} > Prob_{limit}$ subject to $\boldsymbol{\theta}^*$ satisfying the constraints represented in the set Θ.

6.2 Stochastic Optimization with Different Criteria in Retail Building Case 2

This section will search for the optimal investment solution in recognition of uncertainties in physical parameters, usage scenarios, cost models, productivity loss, future demand charge rates that are listed in Table 5.2. The stochastic optimization will be carried out with the @Risk software already introduced in earlier Chapters. This section illustrates how different optimization criteria proposed in section 6.1 may lead to distinctly different optimal EEM+EFM selection. As a first example, we inspect Figure 4.80, showing results for the retail building, case 2 model. It reveals that the NPV of the investments at budget levels 2 to 5 differ from each other only by a small amount. It would, therefore, be interesting to see whether the optimal choice of measures changes (suggesting different budget level) when we add uncertainty and optimize for the different criteria. This will be inspected below.

6.2.1 Expected Mean of the NPV

The optimization algorithm searches for the optimal set with the stochastic criterion that the investor wants to maximize the expected mean value of the NPV (criterion 1). The optimization result shown in Figure 6.1 reveals that is the maximum expected value of the NPV is $930,000 with the standard deviation of $34,500.

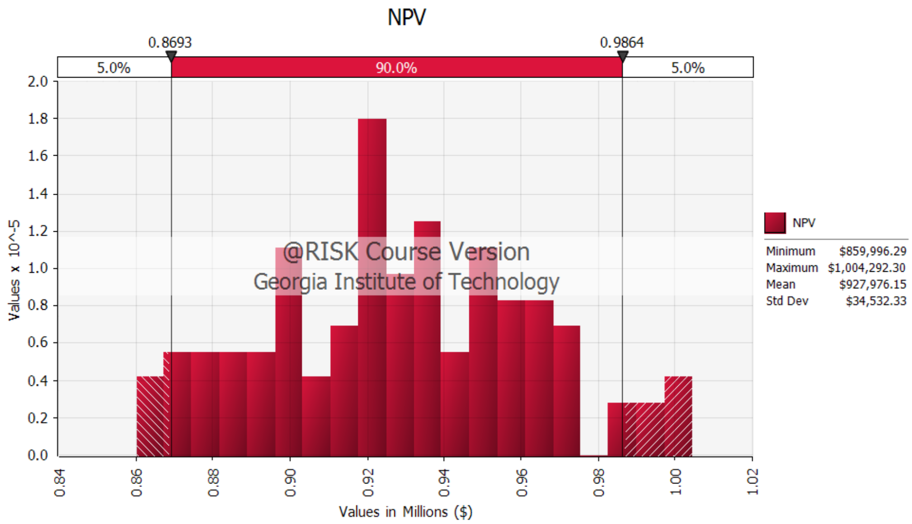


Figure 6.1 Distribution of the NPV with criterion 1

6.2.2 Magnitude of the NPV Deviation

In this subsection, the optimization algorithm searches for the optimal set with the stochastic criterion that the investor wants to maximize the expected mean value of NPV with the constraint that the standard deviation of the NPV is not more than 30,000 (criterion 2). The optimization result shown in Figure 6.2 reveals that is the maximum expected value of the NPV is $887,500 with the standard deviation of $29,350. Table 6.1 reveals that the total initial investment cost if optimized with criterion 2 is lower than with criterion 1. By comparing the result of Figure 6.1 and Figure 6.2, we find that the expected mean value of the NPV that we find with criterion 1 is higher than with criterion 2. As expected, criterion 2 results in a less dispersed distribution, at the cost of a slightly lower expected mean of NPV. An analysis of how this changes the optimal set of EEM+EFM is shown in Table 6.1.

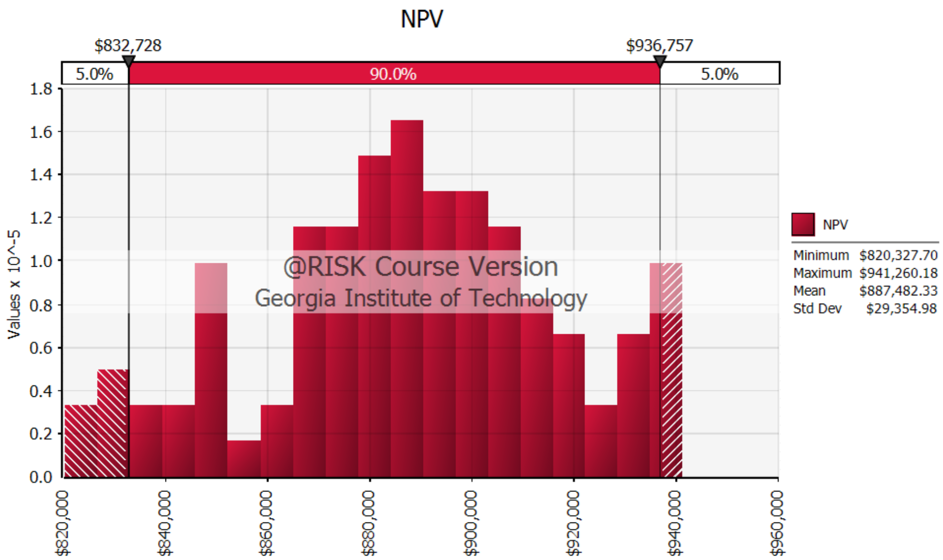


Figure 6.2 Distribution of the NPV with criterion 2

6.2.3 Minimizing Downside Risk (criterion 3)

In this subsection, the optimization algorithm searches for the optimal set with the stochastic criterion that the investor wants to maximize the mean value of NPV with the constraint that the probability that NPV is greater than $900,000 is at least 80% (criterion 3). The optimization result shown in Figure 6.3 reveals that the mean value of the NPV is $927,700 with the standard deviation of $32,284 with the 80% probability that NPV is greater than $900,000.

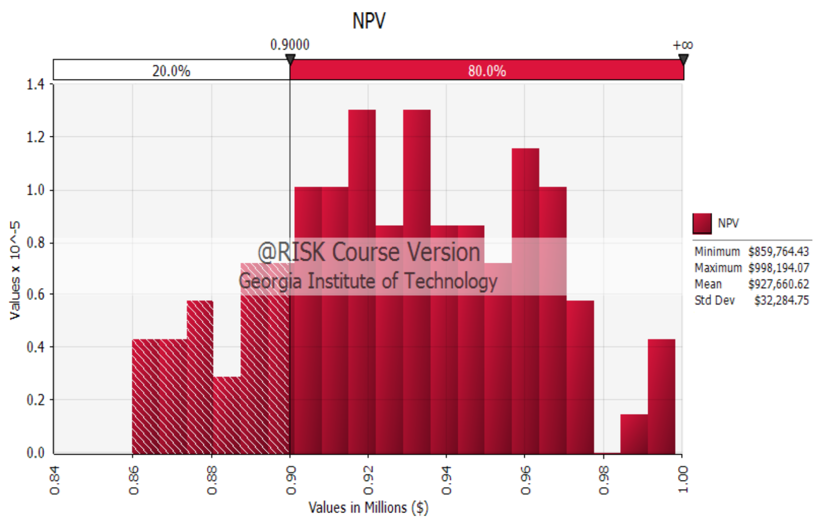


Figure 6.3 Distribution of the NPV with criterion 3

An analysis of how this changes the optimal set of EEM+EFM is shown in Table 6.1.

6.2.4 Summary of the Stochastic Optimization with a Different Criterion.

Figure 6.4 shows box plots of the NPV with the three criteria. Criterion 1 has the maximum mean value of the NPV, criterion 2 has the lowest NPV and the lowest standard deviation, and criterion 3 has the maximum probability that the NPV is higher than $900,000.

Table 6.1 details the investment strategy in the stochastic optimization study with different optimization criteria. It indicates that the optimal investment decision varies under different optimization criteria.

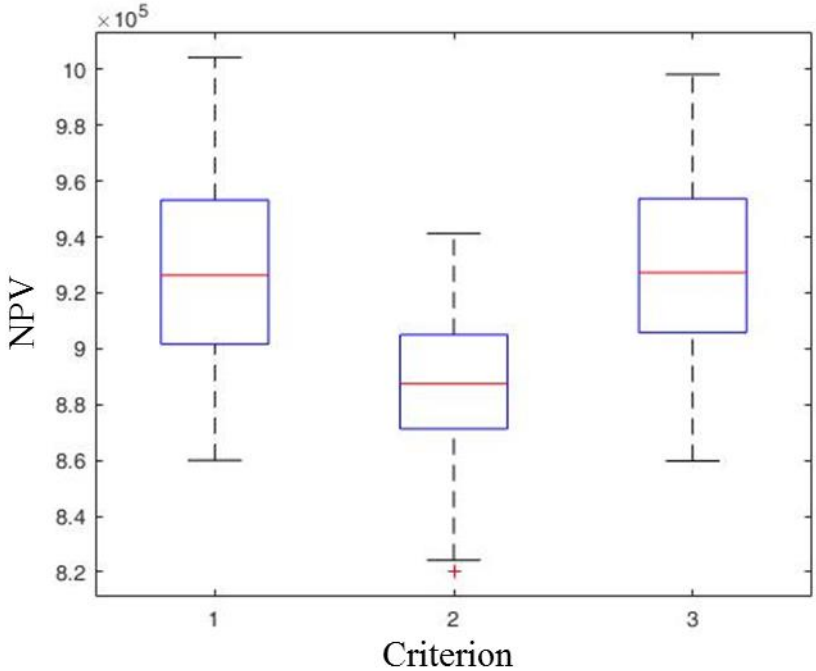


Figure 6.4 Box plot of stochastic optimization with three criteria

Table 6.1 Investment in the retail building case 2 with different optimization criterion

Stochastic Optimization		EEMs					EFMs				Total
		Infiltration Rate	Insulation Thickness	Emissivity of Roof	Solar Reduction Factor	Window SHGC	Temperature Control	Lighting Dimmer	Voltage Throttling	PV System	
Criterion	(1)	-	9000	7,500	24,200	176,000	-	7,800	-	104,000	328,500
	(2)	5400	19,200	7,500	24,200	150,000	-	7,800	-	7,280	221,380
	(3)	-	10,500	7,500	24,200	176,000	-	7,800	-	104000	330,000

6.3 Stochastic Optimization with Different Criteria in Retail Building Case 5

This section will search for the optimal investment solution in recognition of uncertainties in physical parameters, usage scenarios, cost models, productivity loss, future demand charge rates that are listed in Table 5.2. This section inspects Figure 4.92, showing results for the retail building, case 5 model with different optimization criterion.

6.3.1 *Expected Mean of the NPV*

The optimization algorithm searches for the optimal set with the stochastic criterion that the investor wants to maximize the expected mean value of the NPV (criterion 1). The optimization result shown in Figure 6.5 reveals that is the maximum expected value of the NPV is $752,000 with the standard deviation of $61,000.

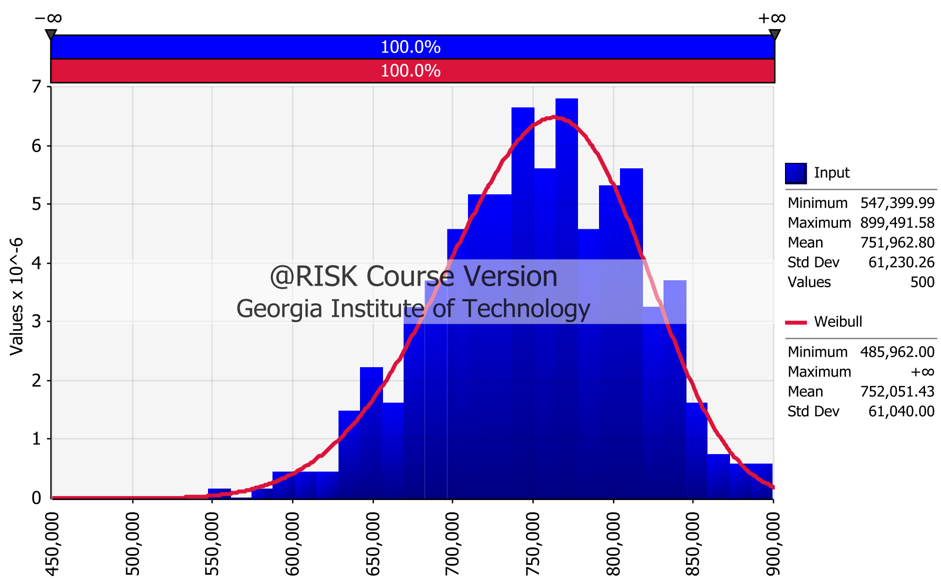


Figure 6.5 Distribution of the NPV with criterion 1

6.3.2 *Magnitude of the NPV Deviation*

In this subsection, the optimization algorithm searches for the optimal set with the stochastic criterion that the investor wants to maximize the expected mean value of NPV with the constraint that the standard deviation of the NPV is not more than 58,500 (criterion 2). The optimization result shown in Figure 6.6 reveals that is the maximum expected value of the NPV is $688,000 with the standard deviation of $58,000. Table 6.2 reveals that the total initial investment cost if optimized with criterion 2 is lower than with criterion 1. By comparing the result of Figure 6.5 and

Figure 6.6, we find that the expected mean value of the NPV that we find with criterion 1 is higher than with criterion 2. As expected, criterion 2 results in a less dispersed distribution, at the cost of a slightly lower expected mean of NPV. An analysis of how this changes the optimal set of EEM+EFM is shown in Table 6.2.

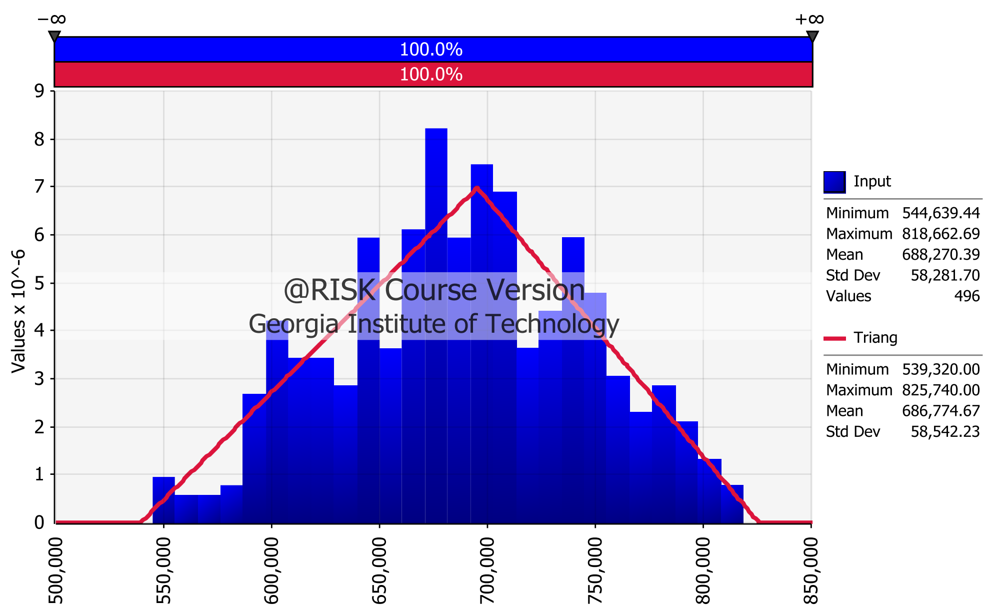


Figure 6.6 Distribution of the NPV with criterion 2

6.3.3 Minimizing Downside Risk (criterion 3)

In this subsection, the optimization algorithm searches for the optimal set with the stochastic criterion that the investor wants to maximize the mean value of NPV with the constraint that the probability that NPV is greater than $700,000 is at least 20% (criterion 3). The optimization result shown in Figure 6.7 reveals that the mean value of the NPV is $749,000 with the standard deviation of $61,500 with the 80% probability that NPV is greater than $700,000.

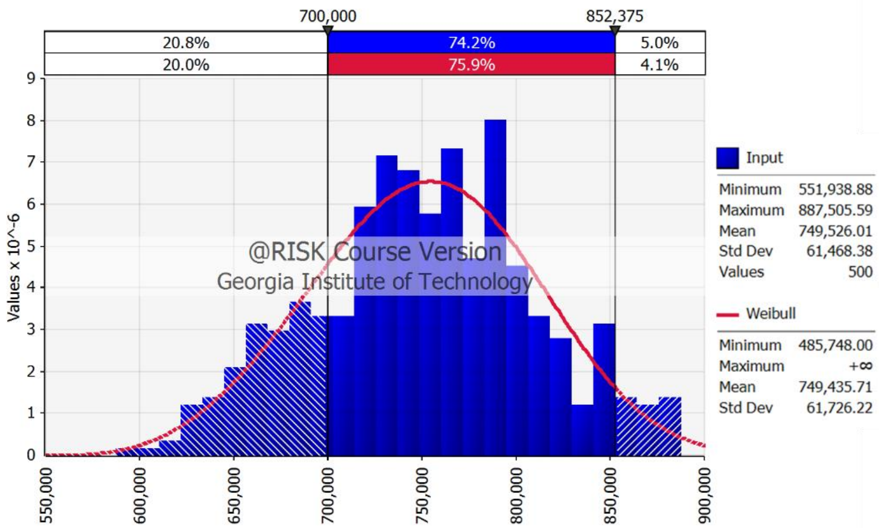


Figure 6.7 Distribution of the NPV with criterion 3

An analysis of how this changes the optimal set of EEM+EFM is shown in Table 6.2.

6.3.4 Summary of the Stochastic Optimization with a Different Criterion.

Figure 6.8 shows box plots of the NPV with the three criteria. Criterion 1 has the maximum mean value of the NPV, criterion 2 has the lowest NPV and the lowest standard deviation, and criterion 3 has the maximum probability that the NPV is higher than $700,000.

Table 6.2 details the investment strategy in the stochastic optimization study with different optimization criteria. It indicates that the optimal investment decision varies under different optimization criteria.

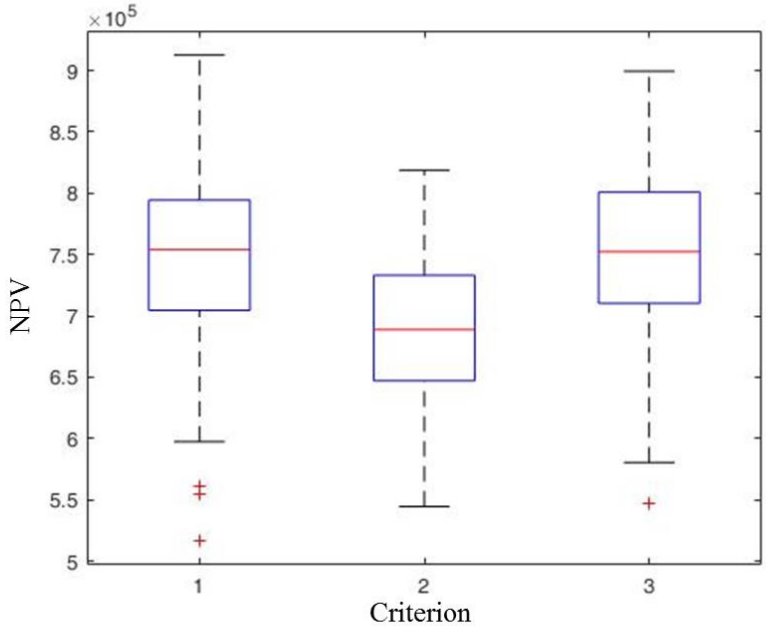


Figure 6.8 Box plot of stochastic optimization with three criteria

Table 6.2 Investment in the retail building case 2 with different optimization criterion

Stochastic Optimization		EEMs					EFMs				Total
		Infiltration Rate	Insulation Thickness	Emissivity of Roof	Solar Reduction Factor	Window SHGC	Temperature Control	Lighting Dimmer	Voltage Throttling	PV System	
Criterion	(1)	-	14,500	7,500	24,200	176,000	-	7,800	-	104,000	334,000
	(2)	-	9,600	7,500	24,200	176,000	-	7,800	-	7,800	232,900
	(3)	-	18,800	7,500	24,200	176,000	-	7,800	-	104,000	338,300

6.4 Stochastic Optimization with Changing Uncertainty Boundary of Productivity Loss

None of the optimal EEM/EFM set resulting from the analyses in the previous section contains thermostat adjustment or voltage throttling. As has been explained previously. Because an EFM is applied indiscriminately every day the measure leads to temperature floats and thus productivity loss where there is potentially no benefit because the peak load on that day is not in the top peak load days. As addressed in section 4.1.1, this increases productivity loss during normal operational days without high peak demand in the building or power grid. The accumulative productivity loss through all these days leads to an unavoidable negative impact on the total NPV calculation. Therefore, these measures should only be deployed when there is a predicted peak load occurring in the next few hours or under the demand response contract with the power grid. Such dynamic application of an EFM is not studied in this thesis. Another reason is the analysis presented earlier in section 5.1.1, which showed that the productivity loss uncertainty in our comprehensive analysis model has a significant negative impact on NPV. As some of the models that we used in the UQ show a steep drop in productivity with rising temperatures, a long negative tail for the NPV distribution will result if either of the two measures is selected. As this is a somewhat unexpected effect, it is useful to better to understand how severely the optimal investment choice is affected by the uncertainty in the cost of interventions and particularly the cost associated with productivity loss. Since the productivity loss model adopted in the stochastic optimization analysis model is trained with the most “conservative” models reported in the literature, it is worthwhile to inspect the effect of a less conservative model with smaller productivity loss. This is useful to find out what optimistic assumptions would be necessary to put thermostat control and voltage throttling back into the optimal mix. A more optimistic model would, for instance, assume that temperature increases above 24℃ until 27.5 ℃ lead to modest loss of productivity.

In general, it can be stated that the choice of uncertainty ranges of unknown parameters (e.g. in the productivity loss model) will have a large impact on the optimal set. Some methods will in fact not be selected if they lead to a wide dispersed risk that violates the lack of appetite for risk of the decision maker. The larger the uncertainty in the parameters of a measure, the more the measure will add to the dispersedness of the NPV distribution and hence to the likelihood that a set that contains that particular measure will not be found to be optimum. This would explain that a “safe” set of measures will most likely not contain a measure with a risky downside. It is, therefore, worth exploring the possibility that certain measures would be chosen in the optimization analysis if we shrink the range in uncertainty in their parameters based on better knowledge or information. As an example, we will repeat the stochastic optimization of a retail building in rate case 2 under the optimistic assumption that productivity only reduces 5% when the temperature reaches 30 ℃. One could argue that this optimistic assumption is completely arbitrary. Nevertheless, the analysis is useful to show the significance and provide an incentive for more research. Figure 6.9 displays the distribution of the NPV with less conservative productivity loss model. The expected mean of the NPV increased to \$952,000 with a standard deviation of \$30,000. The thermostat control is selected in the optimal mix.

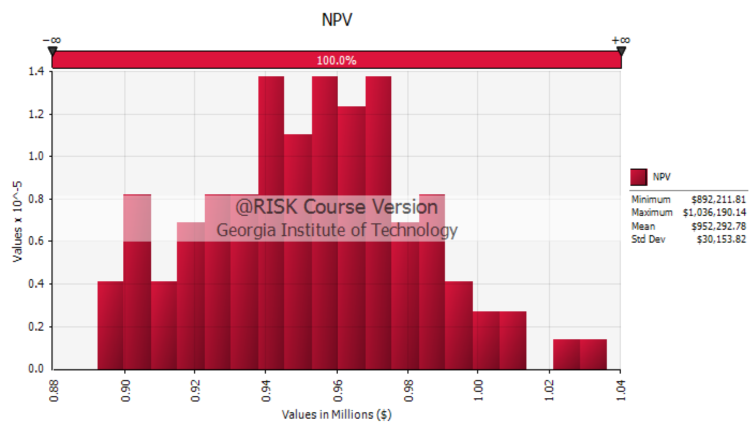


Figure 6.9 Distribution of the NPV with a less conservative productivity loss model

More research in this area is warranted as productivity loss is notoriously hard to measure in an unbiased and objective way, as worker’s actual productivity during the day can hardly remain at 100% throughout the day, but the loss is always reported in relation to a presumed constant 100%. A worker’s true productivity may be 80% in the afternoon, and any thermostat adjustment could have effects that are not well quantified.

6.5 Summary of the Stochastic Optimization

This chapter carries out stochastic optimization with user preference criteria that lead to a rational investment decision (informed by NPV outcome) in the recognition of uncertainties. Section 6.2 and 6.3 explains stochastic optimization under different risk criteria, that can be addressed as different expressions of “robustness”. The outcomes of the optimization reveal that different optimal investments could be found with different optimization criterion. There is indeed no one absolute optimal solution to the problem in the real world which is stochastic in nature.

The study in this chapter concludes that the optimal investment choice is heavily affected by the uncertainty in the cost of interventions. Thermostat adjustment and voltage throttling will never be selected with the high cost associated with productivity loss as reported in current literature. Any solution containing such measure will not lead to an NPV with highest expected mean and moreover increase the downside risk to a level that most decision makers would find intolerable. We should recall at this stage that our study is based on static EFM’s. The presumption is that they are installed by the building operator to be activated at a fixed time, every day. As explained in the introduction, EFM’s can also be implemented in a dynamic way, reacting to predefined circumstances, e.g. thermostat adjustments would only be activated on days that are expected to reach a certain peak power level. For those dynamic scenarios, the conclusions presented here will have to be adjusted. This should be the subject of future research.

An important application of the uncertainty analysis is that it could tell us whether better knowledge about a specific uncertainty parameter is required in order to achieve a certain goal, i.e. control the risk of the outcome within an acceptable range and guarantee the value of savings with a higher confidence.

CHAPTER 7 MODEL VALIDATION

This chapter validates the use of the reduced order model in this study against a higher fidelity model, such as EnergyPlus (Crawley et al. 2000). This task will focus on verifying whether the analysis that underlies the optimization is supported well enough by EPC. As the EPC calculations are based on a reduced order model we cannot be confident that the absolute results are accurate enough for the purposes of EEM/EFM optimal selection. Issues related to EPC accuracy and applicability is discussed in (Lee et al. 2013). The general findings of these studies are that EPC performs well in comparative analyses. As optimization is in essence based on comparative analysis, there is sufficient confidence that the EPC forms a good enough basis for our optimizations. This is particularly true for the calculation of the energy demand (thermal loads). For the electricity consumption of the HVAC system, EPC is however much less suited as the systems consumption calculation only uses a set of macro parameters for each system type. As the optimization uses power as one of the major drivers of cost (in the form of demand charges) we expect to find that the poor system representation in EPC could be a major hurdle in the validation. To pre-empt this, a pre-calibration step is proposed to the HVAC electricity consumption model. The underlying assumption is that future versions of the EPC will have undergone a pre-calibration where the HVAC model is “improved” by a generic set of parameters that represents the system behavior under different system part load. We test the validity of the EPC through the following four steps.

The first step is to pre-calibrate the HVAC system model in EPC with the EnergyPlus model based on hourly energy consumption data through several surrogate system coefficients. The second step is to characterize the hourly load discrepancy between the calibrated EPC and

EnergyPlus model with a time series. The third step is implementing the hourly discrepancy as a model form uncertainty in the EPC model and redo the uncertainty analysis. The fourth step re-runs the stochastic optimization analysis with the added model form uncertainty and determines whether one of the following situations occurs: (1) A different optimal mix is found (2) The extra resulting uncertainty in NPV exceeds reasonable risk bounds from the perspective of the decision maker. Based on the occurrence if either or both of these situations in several test cases, we will draw conclusions regarding the validity of the use of EPC as the underlying calculation in this thesis.

7.1 HVAC System Pre-calibration

This section explains the approach to the pre-calibration. The target is to find the parameters that lead to the best approximation of the electricity consumption simulated with EnergyPlus. For that reason, a given building is modeled in both EnergyPlus and EPC. Special care is taken that the total direct electricity consumers (appliances, lighting) are identical in both models. We base the EPC-EnergyPlyus comparison on hourly data, but it should be noted that the calculation of our primary outcome (NPV) uses only monthly total energy usage and peak load. Therefore, we test two calibration approaches: (1) calibrate for monthly values of integrated consumption and peak load, (2) calibrate for hourly values of the load for every hour of the year. We use both approaches to inspect the change in the accuracy of the calibrated models for the two different types of interval data. To do this in a methodical way, the model calibration is carried out at four distinct levels. The first level is calibration with the monthly total energy consumption data. The second level is calibration with 20% weight on the monthly total and 80% weight on the monthly peak demand. The third level is calibration with the monthly peak demand data. The fourth level is calibration with hourly energy consumption data.

The HVAC system model adopted in EPC is based on ISO 13790 that is generalized for different types of building with different sizes and usage patterns. It approximates the real energy consumption of the HVAC system through a set of “macro-level system coefficient”, which are at best an average representation of a real HVAC system. The underlying assumption is that enough data is available to determine which parameter values capture a given HVAC system. In the current version of EPC this is not yet accomplished, hence the need for a customized pre-calibration for our prototype buildings and their specific systems. We select seven system coefficients to serve as the calibration parameters, i.e. four chiller COP coefficient that characterizes the performance curve of the chiller under different system cooling load fractions, two fan power factors that represent the efficiency curve of the fan at different part load ratio and one pump correction factor. All coefficients are scaled such that when multiplied with the hourly energy demand of the chiller, fan flow volume, and pump volume the added outcome is the total HVAC system energy consumption.

This approach is tested on the baseline building (budget level 0) of the retail building used in this thesis. Table 7.1 lists the value of each calibration parameter at different calibration levels together with the CVRMSE (coefficient of variation of the root mean square error) of the calibrated model. As this study is focused on demand charge reduction, the reduced order model should have sufficient fidelity of system dynamics to produce a reliable prediction of the monthly peak demand. Therefore, the performance of the pre-calibrated EPC is evaluated at an hourly resolution. The CVRMSE of the baseline EPC model is 0.36. The result reveals that the CVRMSE of the calibrated model reduces with increased weight on the monthly peak. The hourly calibration model has the best performance against the other three calibrated model, which can reduce the CVRMSE to 0.21.

The hourly calibrated model is consequently deemed the most appropriate to be used for the analysis of the next steps.

Table 7.1 Pre-calibration parameter values and CVRMSE of the hourly difference in load calculated by EPC and EnergyPlus

	Chiller COP coefficient 1	Chiller COP coefficient 2	Chiller COP coefficient 3	Chiller COP coefficient 4	Fan power factor1	Fan Power factor 2	Pump correction factor	CVRMSE
Original model	1	0.9	0.82	0.5	1	1	8	0.36
Calibrated on monthly total	1.16	1.38	1.23	1.1	1.23	1.52	6.8	0.35
Calibrated on weighted monthly total and peak	1.17	1.13	1.34	1.26	1.68	1.19	6.9	0.32
Calibrated on monthly peak	1.31	1.3	1	1.03	1.34	1.28	9	0.31
Calibrated on hourly	1.57	1.88	1.42	0.84	1.16	1.02	2	0.21

7.2 Quantify the Model Form Uncertainty

With the pre-calibrated EPC model based on hourly energy consumption data, we can now quantify the hourly discrepancy (henceforth called “diff”) between the EPC and EnergyPlus model. We treat the diff as a separate time series for each day of the year. With 8760 hourly diff values, we train 365 stochastic models for the time series of each day. Figure 7.1 displays the hourly diff between calibrated and uncalibrated EPC and EnergyPlus. The Brownian motion mean reversion model (Nexus 1978) is selected to characterize the hourly diff. Figure 7.2 displays the time series fit of the diff in one day. The diff is now treated as model form uncertainty in EPC. With this added source of uncertainty in the EPC, the next subsection will repeat the UA and stochastic optimization carried out in previous chapters. This will reveal the validity (or at least the adequacy) of the EPC to carry out these studies.

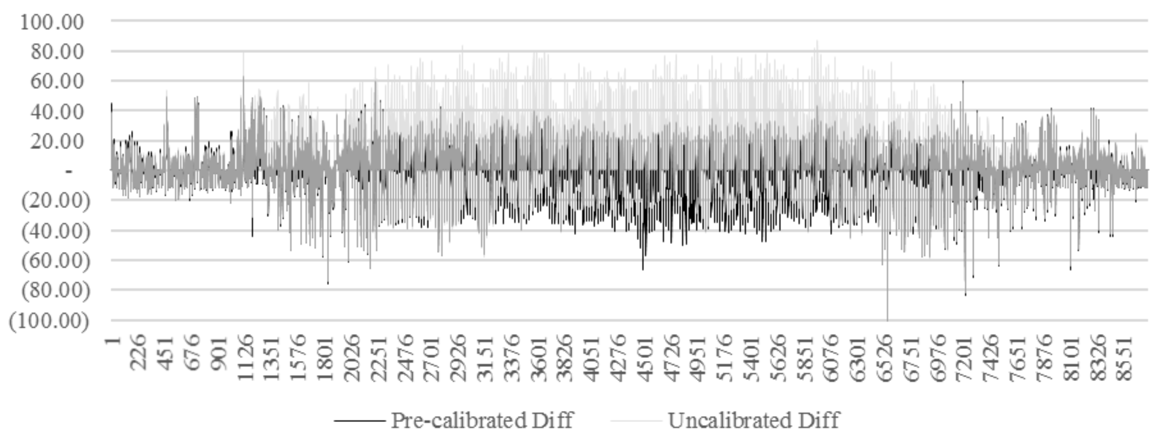


Figure 7.1 Diff [kW] between calibrated and uncalibrated EPC and EnergyPlus

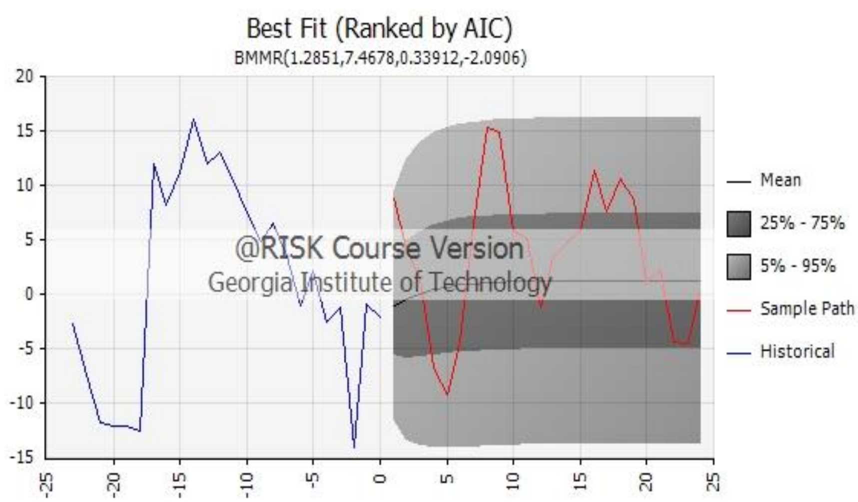


Figure 7.2 Time series fit of the daily diff

7.3 Distribution of NPV

This section shows the uncertainty analysis result with the diff (as model form uncertainty) added into the EPC model.

7.3.1 Retail Building, Case 2 Uncertainty Analysis with Incorporation of Diff

We conduct the analysis for optimal EEM/EFM set that led to the highest NPV for the retail building under rate structure case 2 (section 4.3). The same uncertainty analysis is conducted as before with the only difference that the hourly diff (time series) is added to the EPC and inspect what its the influence is on the NPV distribution, before pre-calibration, and after pre-calibration. Figure 7.3, Figure 7.4 and Figure 7.5 show the distribution of NPV, respectively without adding the model form uncertainty, with the uncalibrated model form uncertainty, and with the pre-calibrated model form uncertainty. The results reveal that with the model form uncertainty added in, the mean value of the NPV slightly increases, which is caused by the energy consumption predicted in EnergyPlus is lower than in EPC. As expected the standard deviation and the base of the NPV distribution increases with the model form uncertainty added in. The calibrated model reduces the range of the distribution, and in fact, significantly reduces the standard deviation from $90,000 to $45,000. A preliminary conclusion based on this case analysis is that the increase in uncertainty in the outcome of the NPV of the pre-calibrated EPC is minor compared to the original model used in the analysis of the previous chapters. In particular, adding the model form uncertainty does not lead to long tails on either end of the distribution. This leads to the cautious preliminary conclusion that the use of EPC is validated. However, this is no guarantee that the model with added diff will also lead to the same optimal set when we perform stochastic optimization. The next section will inspect how the increased uncertainty in NPV impacts the stochastic optimum in the presence of certain stochastic criterion. In particular, it needs to be verified whether a certain optimum from the previous chapters is no longer valid as it can not meets a criterion 3 risk threshold set by the decision maker.

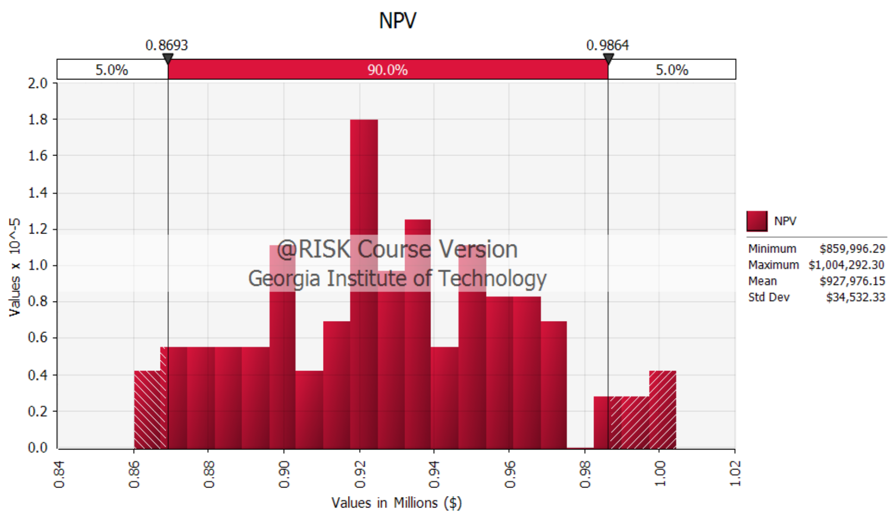


Figure 7.3 Distribution of NPV without model form uncertainty (refer to Figure 6.1)

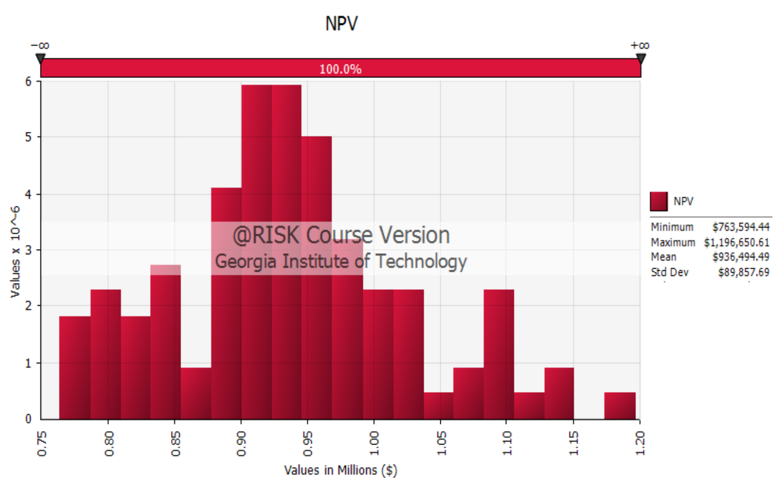


Figure 7.4 Distribution of NPV with added diff but without pre-calibration

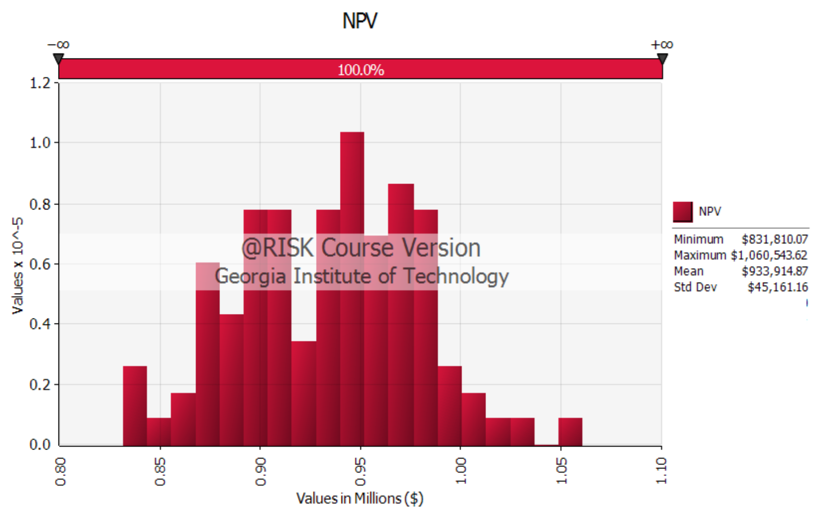


Figure 7.5 Distribution of NPV with added diff and with pre-calibration

7.3.2 Retail building, Case 2 Stochastic Optimization with Incorporation of Diff

In this subsection, we inspect whether the increased uncertainty range of NPV will impact the optimal mix of measures and whether in certain cases the optimum does not exist as no set is able to meet a certain risk acceptance threshold as earlier characterized as risk criterion 3. Figure 7.6, Figure 7.7, and Figure 7.8 show the same distributions of NPV as shown above but it now indicates the probability that the NPV is above 0.9 million in each figure. Assuming that this represents the risk criterion of the decision maker (the probability of NPV >.9 million should be at least 80%), the results reveal that in the uncalibrated model with the model form uncertainty added in, the optimal combination of measures does no longer meet criterion 3, as the probability of NPV>0.9M is only 69% (Figure 7.7). However, in the calibrated model with the model form uncertainty added in, the optimal solution can guarantee 79% probability that the NPV is larger than 0.9M. This is very close to the 80% threshold. Again, the preliminary conclusion from this test is that the pre-calibrated EPC can produce reliable outcomes in NPV even though the diff (hourly load discrepancy) has a relatively large CVRMSE of 0.21. It could be expected that with the addition of more pre-calibrated parameters, the diff could become smaller and hence an even smaller contribution to the uncertainty of NPV could be expected.

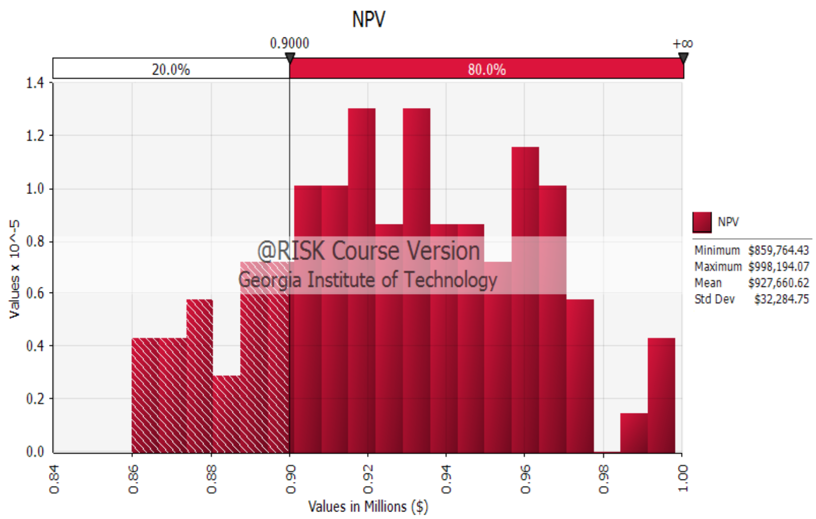


Figure 7.6 Distribution of NPV without model form uncertainty

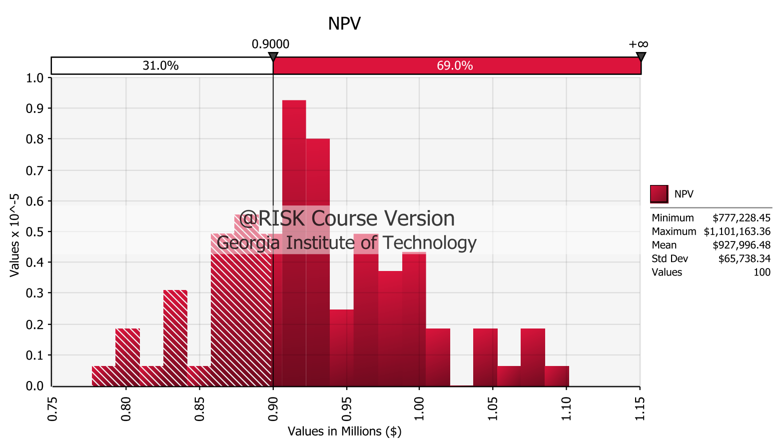


Figure 7.7 Distribution of NPV without calibration of EPC

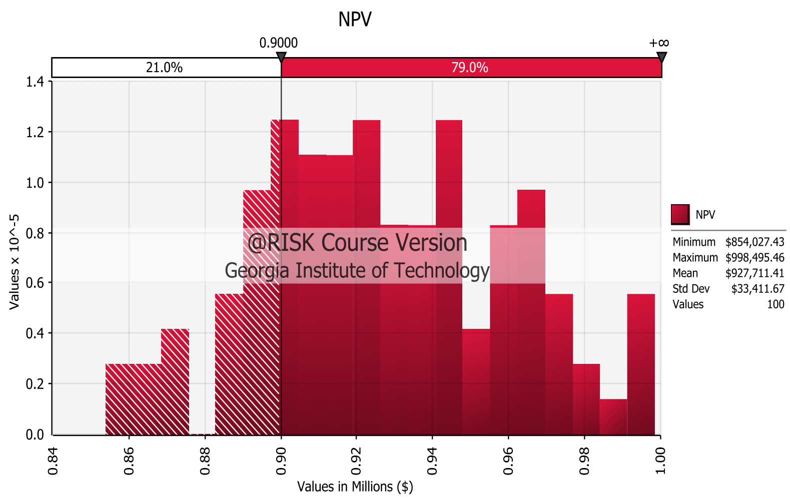


Figure 7.8 Distribution of NPV with calibration of EPC

7.3.3 Retail Building, Case 5 Uncertainty Analysis with Incorporation of Diff

We conduct the analysis for optimal EEM/EFM set that led to the highest NPV for the retail building under rate structure case 5 (section 4.3). The same uncertainty analysis is conducted as before with the only difference that the hourly diff (time series) is added to the EPC and inspect what its the influence is on the NPV distribution, before pre-calibration, and after pre-calibration. Figure 7.9 shows the distribution of NPV, respectively without adding the model form uncertainty, with the uncalibrated model form uncertainty, and with the pre-calibrated model form uncertainty. The results reveal that with the model form uncertainty added in, the mean value of the NPV slightly increases, which is caused by the energy consumption predicted in EnergyPlus is lower than in EPC. As expected the standard deviation and the base of the NPV distribution increases with the model form uncertainty added in. The calibrated model reduces the range of the distribution, and in fact, significantly reduces the standard deviation from $65,000 to $63,000.

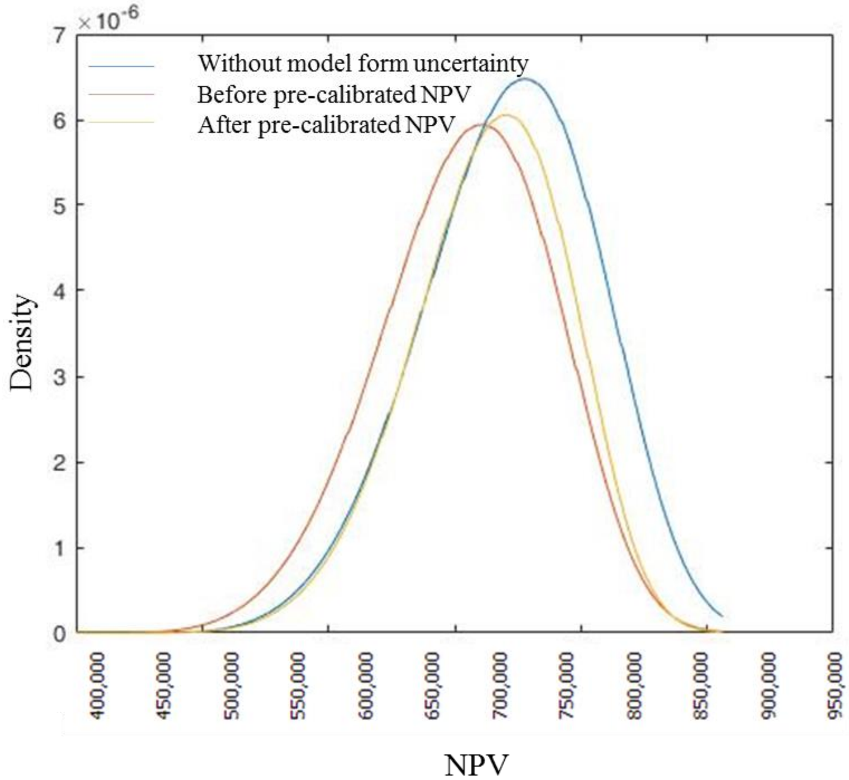


Figure 7.9 Distribution of NPV

7.3.4 Retail Building, Case 5 Stochastic Optimization with Incorporation of Diff

In this subsection, we inspect whether the increased uncertainty range of NPV will impact the optimal mix of measures and whether in certain cases the optimum does not exist as no set is able to meet a certain risk acceptance threshold as earlier characterized as risk criterion 3. Figure 7.10 shows the same distributions of NPV as shown above but it is now indicate the probability that the NPV is above 0.7 million in each figure. Assuming that this represents the risk criterion of the decision maker (the probability of NPV > 0.7 million should be at least 80%), the results reveal that in the uncalibrated model with the model form uncertainty added in, the optimal combination of measures does no longer meet criterion 3, as the probability of NPV > 0.7 million is only 68 %. However, in the calibrated model with the model form uncertainty added in, the optimal solution can guarantee 78% probability that the NPV is larger than 0.7M. This is very close to the 80% threshold.

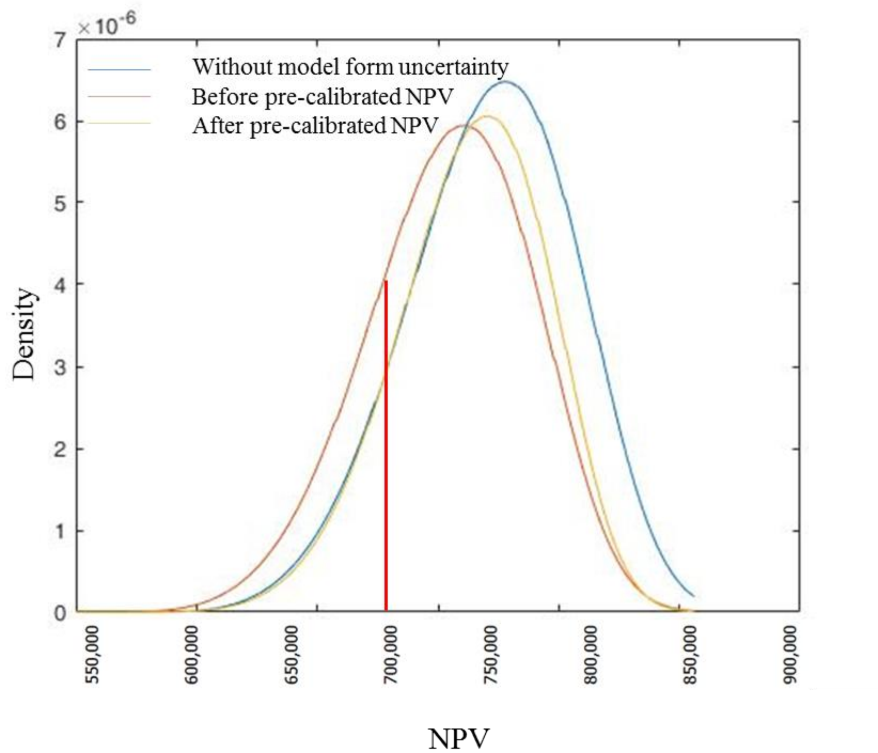


Figure 7.10 Distribution of NPV

7.4 Stochastic Optimization with Model Form Uncertainty

With the model form uncertainty added in EPC, we can redo the stochastic optimization. Table 7.2 shows the new optimum EEM/EFM for two cases: (a) stochastic optimization with criterion 1; (b) stochastic optimization with criterion 3. They are both compared with the optimum found in the previous chapter. As can be seen, in case (a) the optimum for criterion 1 is not affected by the addition of the extra model form uncertainty. However, for case (b) the optimum for criterion 3 is affected because as we anticipated from Figure 7.7 (the old optimum does no longer satisfy the downside risk criterion) a new optimum is found. The table shows the new set of optimum EEM/EFM that is found.

Table 7.2 Investment in the retail building case 2 with different optimization criterion

Stochastic Optimization	EEMs					EFMs				Total
	Infiltration Rate	Insulation Thickness	Emissivity of Roof	Solar Reduction Factor	Window SHGC	Temperature Control	Lighting Dimmer	Voltage Throttling	PV System	
Criterion (1)	-	9,000	7,500	24,200	176,000	-	7,800	-	104,000	328,500
Criterion (3)	10,000	13,000	7,500	24,200	176,000	Yes	7,800	-	104,000	342,500

Figure 7.11 and Figure 7.12 show the NPV result for the optimum set resulting from the stochastic optimization for the retail building case. The results reveal that, if the optimization is performed with the calibrated model and added diff, the same or a new optimum is found that meet the risk criterion. Obviously, the NPV value has changed with the added model form uncertainty.

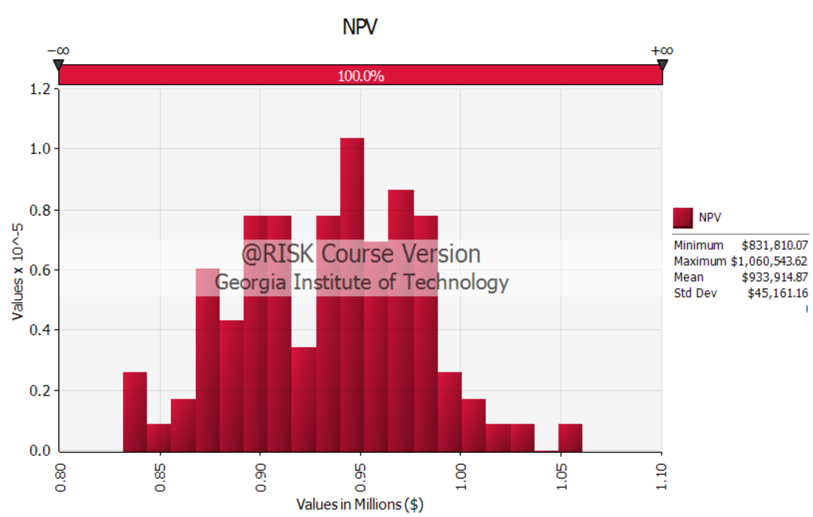


Figure 7.11 Distribution of the NPV of stochastic optimum found with added diff and applying criterion 1

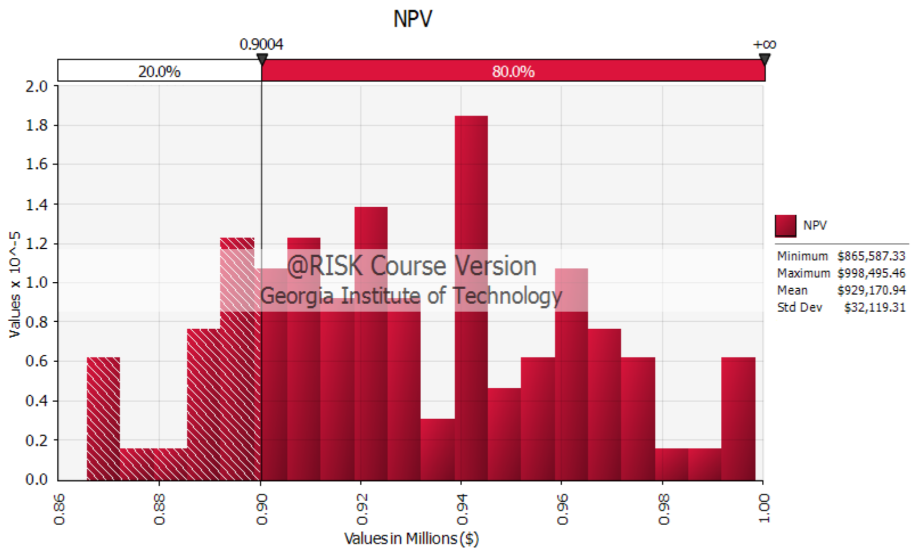


Figure 7.12 Distribution of the NPV of stochastic optimum found with added diff and applying criterion 3

The results found for the retail building point to the preliminary conclusion that a pre-calibrated EPC with added diff (characterized by comparison with EnergyPlus) is adequate for the analysis performed in this thesis. Future work needs to repeat this for more cases in order to arrive at a general confirmation of the validity of EPC for this purpose.

CHAPTER 8 CONCLUSION AND FUTURE WORK

8.1 Summary and Conclusions

This thesis analyzes the importance of demand charges in monthly utility bills and explores optimal solutions to reduce peak demand in three different types of commercial buildings.

This thesis introduces five different utility rate structures and analyzes the optimal investment in a range of measures in three types of commercial buildings under different rate structures. Chapter 4 shows the result of deterministic optimization of EEM and EFM in three types of commercial buildings. We find that the rate structure has a significant impact of the cost-effectiveness of interventions. For example, the PV investment is typically considered to be a cost-effective investment based on energy savings alone. This changes at high capacity installations when there is a substantial amount of excess generation. In that case, the economic viability depends strongly on the local feed-in rate or the cost of local storage. Particular rate structure can, in fact, be a disincentive for PV installation, such as the GP PLM-11.

The uncertainty analysis in Chapter 5 has revealed important information which sources of uncertainties have a significant impact on the resulting NPV on chosen measures.

This thesis conducts stochastic optimization under different risk criteria in Chapter 6. The outcomes of the optimization reveal that different optimal investments could be found with different optimization criterion. There is indeed no one absolute optimal solution to the problem in the real world which is stochastic in nature. The optimal investment choice is affected by the uncertainty in the cost of interventions. An important application of the uncertainty analysis is that it could tell us whether better knowledge about a specific uncertainty parameter is required in order to achieve a certain goal. This is particularly so with respect to the productivity loss prediction in certain temperature float scenarios.

The model validation in Chapter 7 concludes that a well calibrated low fidelity model can produce reliable outcomes in peak demand and total energy estimation. The diff between the low fidelity model and high fidelity model (in this case EnergyPlus) can be characterized as a model form uncertainty that is added into the EPC. There is a tradeoff between the model accuracy and model form uncertainty. More efforts spend to improve the accuracy of the model, the less dispersed risk of the model form uncertainty.

8.2 Recommendations for Future Study

To better facilitate the decision making in demand charge reduction attempts by commercial building owners, this thesis recommends future following studies on the following issues:

(1) Generalization of the findings, i.e. for building size, type, rate structure, etc. As size is an important factor in demand charge analysis, the future study could explore that whether a building with larger size indeed spends more money with the same amount of demand charge savings compared to the smaller one, which would question the fairness of current rate structure design since the intensity of peak demand in a large building is the same as in a small building while the demand charges are substantially higher. With the tool developed in this thesis, a generalized relationship between building size, type, and the peak demand could be developed.

(2) A deeper inspection of productivity loss model in order to remove a major source of uncertainty from the optimization. Existing studies have come up with conservative

estimates of productivity loss in higher temperatures. The experiment results collected from these studies are limited to laboratory conditions where they examine effects of temperature on the performance of some mental and other tasks simulating office work. The fitness of applying the experiment data to performance in actual office environments is not clear. If we integrate the productivity loss uncertainty in our comprehensive uncertainty analysis model, it will obviously add a long tail of negative impact on the NPV, which creates a long negative tail for the NPV distribution. This, in turn, makes the choice of these measures an improbable part of the optimal set. Due to its heavy impact on the financial risk analysis of the NPV, an improved productivity loss model with deeper inspection is recommended as future work.

(3) In this thesis, only static, i.e. “pre-programmed” energy flexibility measures have been considered. This is one of the reasons that the role of productivity loss plays a dominant role as it is quite likely that the temperature float measures are applied on days that do not affect the demand charges. Such measures are therefore better deployed as dynamic measures that respond to certain signals and are only implemented on certain days. This should be studied in the next follow-up if this study.

(4) Stochastic optimization for more types of building under different rate structure. Due to the limitation of time, this thesis only conducts the stochastic optimization for one type of commercial building under one specific rate structure. More work needs to be done to extend the stochastic optimization to more types of buildings under different rate structures. A future study could develop a generalized model form uncertainty based on different building and system types that characterize the diff between reducing order model and higher fidelity model.

(5) As a by-product of this thesis, the development has started of a DIY tool for commercial building owners to find the optimal choice among design and operational measures in a retrofit or new design project that delivers the most effective way of reducing demand charges and increasing energy flexibility of commercial buildings. This tool will be a natural extension of the EPC which is already used increasingly for other applications. Its simplicity to model the building is the main reason for the development path chosen in this thesis.

APPENDIX A GEORGIA POWER PLM-11

ELECTRIC SERVICE TARIFF:

POWER AND LIGHT MEDIUM
SCHEDULE: "PLM-11"

GEORGIA POWER
A SOUTHERN COMPANY

PAGE	EFFECTIVE DATE	REVISION	PAGE NO.
1 of 3	With Bills Rendered for the Billing Month of January, 2016	Original	4.00

AVAILABILITY:

Throughout the Company's service area from existing lines of adequate capacity.

APPLICABILITY:

To all electric service of one standard voltage required on the customer's premises, delivered at one point and metered at or compensated to that voltage for any customer with a demand, as determined under the Special Applicability Provisions, of not less than 30 kW but less than 500 kW.

TYPE OF SERVICE:

Single or three phase, 60 hertz, at a standard voltage.

MONTHLY RATE:

Energy Charge Including Demand Charge

Basic Service Charge $19.00

All consumption (kWh) not greater than 200 hours times the billing demand:
- **First 3,000 kWh..11.2561¢ per kWh**
- **Next 7,000 kWh ....10.3091¢ per kWh**
- **Next 190,000 kWh ....8.8885¢ per kWh**
- **Over 200,000 kWh..6.8955¢ per kWh**

All consumption (kWh) in excess of 200 hours and not greater than 400 hours times the billing demand..1.1437¢ per kWh

All consumption (kWh) in excess of 400 hours and not greater than 600 hours times the billing demand..0.8606¢ per kWh

All consumption (kWh) in excess of 600 hours times the billing demand..0.7486¢ per kWh

Minimum Monthly Bill:

A. $19.00 Basic Service Charge plus $8.24 per kW of billing demand in excess of 30 kW, plus excess kVAR charges, plus Environmental Compliance Cost Recovery, plus Nuclear Construction Cost Recovery, plus appropriate Demand Side Management Schedule, plus Fuel Cost Recovery as applied to the current month kWh, plus Municipal Franchise Fee.

B. Metered Outdoor Lighting: The lesser of (1) that determined from paragraph "A" above, or (2) $42.44 per meter plus Environmental Compliance Cost Recovery, plus Nuclear Construction Cost Recovery, plus appropriate Demand Side Management Schedule, plus Fuel Cost Recovery, plus Municipal Franchise Fee for metered outdoor lighting installations, provided service is limited to the lighting equipment itself and such incidental load as may be required to operate coincidentally with the lighting equipment.

APPENDIX B PACIFIC GAS & ELECTRICITY A-10 OPTION A

Pacific Gas and Electric Company
San Francisco, California
U 39

	Revised	*Cal. P.U.C. Sheet No.*	37993-E
Cancelling	Revised	*Cal. P.U.C. Sheet No.*	37478-E

ELECTRIC SCHEDULE A-10
MEDIUM GENERAL DEMAND-METERED SERVICE

Sheet 4

RATES: Standard Non-Time-of-Use Rates

Table A (Cont'd.)

UNBUNDLING OF TOTAL RATES

Customer/Meter Charge Rates: Customer and Meter charge rates provided in the Total Rate section above are assigned entirely to the unbundled distribution component.

Demand Rate by Components ($ per kW)	Secondary Voltage		Primary Voltage		Transmission Voltage	
Generation:						
Summer	$4.89	(I)	$4.28	(I)	$3.37	(I)
Winter	$0.00		$0.00		$0.00	
Distribution:**						
Summer	$6.18	(R)	$5.90	(R)	$1.12	(R)
Winter	$3.74	(R)	$4.04	(R)	$1.12	(R)
Transmission Maximum Demand*	$5.71		$5.71		$5.71	
Reliability Services Maximum Demand*	$0.00	(R)	$0.00	(R)	$0.00	(R)

Energy Rate by Components ($ per kWh)	Secondary Voltage		Primary Voltage		Transmission Voltage	
Generation:						
Summer	$0.10492	(I)	$0.09664	(I)	$0.08800	(I)
Winter	$0.08055	(I)	$0.07537	(I)	$0.06946	(I)
Distribution:**						
Summer	$0.03077	(R)	$0.02968	(R)	$0.00573	(R)
Winter	$0.01854	(R)	$0.02037	(R)	$0.00573	(R)
Transmission Rate Adjustments* (all usage)	$0.00472	(I)	$0.00472	(I)	$0.00472	(I)
Public Purpose Programs (all usage)	$0.01416	(I)	$0.01383	(I)	$0.01342	(I)
Nuclear Decommissioning (all usage)	$0.00149	(I)	$0.00149	(I)	$0.00149	(I)
Competition Transition Charges (all usage)	$0.00100	(R)	$0.00100	(R)	$0.00100	(R)
Energy Cost Recovery Amount (all usage)	($0.00001)	(I)	($0.00001)	(I)	($0.00001)	(I)
DWR Bond (all usage)	$0.00549	(I)	$0.00549	(I)	$0.00549	(I)
New System Generation Charge (all usage)**	$0.00238	(I)	$0.00238	(I)	$0.00238	(I)
California Climate Credit (all usage)***	($0.00378)	(R)	($0.00370)	(R)	($0.00266)	

* Transmission, Transmission Rate Adjustments, and Reliability Service charges are combined for presentation on customer bills.

** Distribution and New System Generation Charges are combined for presentation on customer bills.

*** Only customers that qualify as Small Businesses – California Climate Credit under Rule 1 are eligible for the California Climate Credit.

(Continued)

Advice Letter No: 4902-E-B	*Issued by*	*Date Filed*	December 30, 2016
Decision No.	***Steven Malnight***	*Effective*	January 1, 2017
	Senior Vice President	*Resolution No.*	E-4808
4C8	*Regulatory Affairs*		

APPENDIX C PACIFIC GAS & ELECTRICITY A-10 OPTION B

Pacific Gas and Electric Company		Revised	*Cal. P.U.C. Sheet No.*	37994-E
San Francisco, California	*Cancelling*	Revised	*Cal. P.U.C. Sheet No.*	37479-E
U 39				

ELECTRIC SCHEDULE A-10 Sheet 5
MEDIUM GENERAL DEMAND-METERED SERVICE

RATES: Time-of-Use Rates for Optional or Real-Time Metering Customers

Table B

TOTAL RATES

	Secondary Voltage	Primary Voltage	Transmission Voltage
Total Customer/Meter Charge Rates			
Customer Charge ($ per meter per day)	$4.59959	$4.59959	$4.59959
Optional Meter Data Access Charge ($ per meter per day)	$0.98563	$0.98563	$0.98563
Total Demand Rates ($ per kW)			
Summer	$16.78 (R)	$15.89 (R)	$10.20 (R)
Winter	$9.45 (R)	$9.75 (R)	$6.83 (R)
Total Energy Rates ($ per kWh)			
Peak Summer	$0.21972 (I)	$0.20802 (I)	$0.17154 (I)
Part-Peak Summer	$0.16459 (I)	$0.15746 (I)	$0.12466 (I)
Off-Peak Summer	$0.13652 (I)	$0.13083 (I)	$0.09936 (I)
Part-Peak Winter	$0.13641 (I)	$0.13445 (I)	$0.11287 (I)
Off-Peak Winter	$0.11935 (I)	$0.11857 (I)	$0.09830 (I)
PDP Rates (Consecutive Day and Four-Hour Event Option)*			
PDP Charges ($ per kWh)			
All Usage During PDP Event	$0.90	$0.90	$0.90
PDP Credits			
Demand ($ per kW)			
Maximum Summer	($3.26) (R)	($2.85) (R)	($2.25) (R)
Energy ($ per kWh)			
Peak Summer	($0.00347) (I)	($0.00462) (I)	($0.00821) (R)
Part-Peak Summer	($0.00347) (I)	($0.00462) (I)	($0.00821) (R)
Off-Peak Summer	($0.00347) (I)	($0.00462) (I)	($0.00821) (R)

*See PDP Details, section g, for corresponding reduction in PDP credits and charges if other option(s) elected.

Total bundled service charges shown on customers' bills are unbundled according to the component rates shown below. PDP charges and credits are all generation and are not included below.

(Continued)

Advice Letter No:	4902-E-B	*Issued by*	*Date Filed*	December 30, 2016
Decision No.		***Steven Malnight***	*Effective*	January 1, 2017
		Senior Vice President	*Resolution No.*	E-4808
5C8		*Regulatory Affairs*		

APPENDIX D PACIFIC GAS & ELECTRICITY A-1

Pacific Gas and Electric Company *San Francisco, California* U 39		Revised	*Cal. P.U.C. Sheet No.*	37985-E
	Cancelling	Revised	*Cal. P.U.C. Sheet No.*	37472-E

ELECTRIC SCHEDULE A-1
SMALL GENERAL SERVICE

Sheet 3

TERRITORY: This rate schedule applies everywhere PG&E provides electric service.

RATES: Total bundled service charges are calculated using the total rates shown below. Direct Access (DA) and Community Choice Aggregation (CCA) charges shall be calculated in accordance with the paragraph in this rate schedule titled Billing.

TOTAL RATES

A. Non-Time-of-Use Rates

Total Customer Charge Rates		
Customer Charge Single-phase ($ per meter per day)	$0.32854	
Customer Charge Poly-phase ($ per meter per day)	$0.65708	
Total Energy Rates ($ per kWh)		
Summer	$0.24375	(R)
Winter	$0.18915	(R)

B. Time-of-Use Rates

Total Customer Charge Rates		
Customer Charge Single-phase ($ per meter per day)	$0.32854	
Customer Charge Poly-phase ($ per meter per day)	$0.65708	
Total TOU Energy Rates ($ per kWh)		
Peak Summer	$0.25943	(R)
Part-Peak Summer	$0.23578	(R)
Off-Peak Summer	$0.20842	(R)
Part-Peak Winter	$0.21692	(I)
Off-Peak Winter	$0.19601	(I)

<u>PDP Rates (Consecutive Day and Four-Hour Event Option) *</u>

<u>PDP Charges ($ per kWh)</u>		
All Usage During PDP Event	$0.60	
<u>PDP Credits</u>		
<u>Energy ($ per kWh)</u>		
Peak Summer	($0.00950)	(R)
Part-Peak Summer	($0.00950)	(R)
Off-Peak Summer	($0.00950)	(R)

** See PDP Detail, section g, for corresponding reduction in PDP credits and charges if other option(s) elected.*

(Continued)

Advice Letter No: 4902-E-B	*Issued by*	*Date Filed*	December 30, 2016
Decision No.	**Steven Malnight**	*Effective*	January 1, 2017
	Senior Vice President	*Resolution No.*	E-4808
3C9	*Regulatory Affairs*		

APPENDIX E SOUTHERN CALIFORNIA EDISON TOU-GS-3 CPP

SOUTHERN CALIFORNIA EDISON
An EDISON INTERNATIONAL Company

Southern California Edison		Revised	Cal. PUC Sheet No. 60979-E
Rosemead, California (U 338-E)	Cancelling	Revised	Cal. PUC Sheet No. 60309-E

Schedule TOU-GS-3 Sheet 3

TIME-OF-USE - GENERAL SERVICE - DEMAND METERED

(Continued)

RATES

The rates below will apply to all customers receiving service under this Schedule. In addition, the customer will be charged the applicable rates under Option CPP, Option A, Option B or Option R, as listed below. Except for the portion of the customer's firm load that is designated as the Capacity Reservation Level (CRL), CPP Event Charges and CPP Non-Event Credits will apply to all load greater than 0 kW.

	Delivery Service								Generation[9]	
	Trans[1]	Distrbtn[2]	NSGC[3]	NDC[4]	PPPC[5]	DWRBC[6]	PUCRF[7]	Total[8]	UG**	DWREC[10]
Option CPP										
Energy Charge - $/kWh/Meter/Month										
Summer Season On-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.08819 (I)	0.00000 (I)
Mid-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.05095 (I)	0.00000 (I)
Off-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.03226 (I)	0.00000 (I)
Winter Season On-Peak										
Mid-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.04662 (I)	0.00000 (I)
Off-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.03712 (I)	0.00000 (I)
Customer Charge - $/Meter/Month		446.13 (R)						446.13 (R)		
Demand Charge - $/kW of Billing Demand/Meter/Month										
Facilities Related	4.64 (I)	13.17 (R)						17.81 (I)		
Time Related										
Summer Season - On-Peak		0.00						0.00	17.42 (I)	
Mid-Peak		0.00						0.00	3.43 (I)	
Winter Season - On-Peak		0.00						0.00	0.00	
Mid-Peak		0.00						0.00	0.00	
Voltage Discount, Demand - $/kW										
Facilities Related										
From 2 kV to 50 kV	0.00	(0.21)						(0.21)		
Above 50 kV but below 220 kV	0.00	(7.11) (I)						(7.11) (I)		
At 220 kV	0.00	(13.17) (I)						(13.17) (I)		
Time Related										
From 2 kV to 50 kV	0.00	0.00						0.00	(0.34) (R)	
Above 50 kV but below 220 kV	0.00	0.00						0.00	(0.93) (R)	
At 220 kV	0.00	0.00						0.00	(0.94) (R)	
Voltage Discount, Energy - $/kWh										
From 2 kV to 50 kV	0.00000	0.00000						0.00000	(0.00121) (R)	
Above 50 kV but below 220 kV	0.00000	0.00000						0.00000	(0.00269) (R)	
At 220 kV	0.00000	0.00000						0.00000	(0.00271) (R)	
Power Factor Adjustment - $/kVAR										
Greater than 50 kV		0.47						0.47		
50 kV or less		0.55						0.55		
California Alternate Rates for Energy Discount - %		100.00*						100.00*		
CPP Event Energy Charge - $/kWh									1.37453	
Summer CPP Non-Event Credit										
On-Peak Demand Credit - $/kW									(11.44)	
Maximum Available Credit - $/kW**										
On-Peak									(19.81) (R)	
Mid-Peak									(3.90) (R)	

(Continued)

(To be inserted by utility)	Issued by	(To be inserted by Cal. PUC)
Advice 3515-E-A	Caroline Choi	Date Filed Dec 21, 2016
Decision	Senior Vice President	Effective Jan 1, 2017
3C10		Resolution

APPENDIX F SOUTHERN CALIFORNIA EDISON TOU-GS-3 OPTION A

SOUTHERN CALIFORNIA EDISON
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Southern California Edison | Revised Cal. PUC Sheet No. 60980-E
Rosemead, California (U 338-E) | Cancelling Revised Cal. PUC Sheet No. 60310-E

Schedule TOU-GS-3 | Sheet 4

TIME-OF-USE - GENERAL SERVICE - DEMAND METERED

(Continued)

RATES (Continued)

	Delivery Service								Generation[9]	
	Trans[1]	Distrbtn[2]	NSGC[3]	NDC[4]	PPPC[5]	DWRBC[6]	PUCRF[7]	Total[8]	UG**	DWREC[10]
Option A										
Energy Charge - $/kWh/Meter/Month										
Summer Season On-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.28916 (I)	0.00000 (I)
Mid-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.08281 (I)	0.00000 (I)
Off-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.03226 (I)	0.00000 (I)
Winter Season On-Peak										
Mid-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.04662 (I)	0.00000 (I)
Off-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.03712 (I)	0.00000 (I)
Customer Charge - $/Meter/Month		446.13 (R)						446.13 (R)		
Demand Charge - $/kW of Billing Demand/Meter/Month										
Facilities Related	4.64 (I)	13.17 (R)						17.81 (I)		
Voltage Discount, Demand - $/kW										
Facilities Related										
From 2 kV to 50 kV	0.00	(0.21)						(0.21)		
Above 50 kV but below 220 kV	0.00	(7.11) (I)						(7.11) (I)		
At 220 kV	0.00	(13.17) (I)						(13.17) (I)		
Voltage Discount, Energy - $/kWh										
From 2 kV to 50 kV	0.00000	0.00000						0.00000	(0.00192) (R)	
Above 50 kV but below 220 kV	0.00000	0.00000						0.00000	(0.00461) (R)	
At 220 kV	0.00000	0.00000						0.00000	(0.00466) (R)	
Power Factor Adjustment - $/kVAR										
Greater than 50 kV		0.47						0.47		
50 kV or less		0.55						0.55		
California Alternate Rates for Energy Discount - %		100.00*						100.00*		

(Continued)

(To be inserted by utility)
Advice 3515-E-A
Decision

Issued by
Caroline Choi
Senior Vice President

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APPENDIX G SOUTHERN CALIFORNIA EDISON TOU-GS-3 OPTION B

SOUTHERN CALIFORNIA EDISON
An EDISON INTERNATIONAL Company

Southern California Edison — Revised Cal. PUC Sheet No. 60981-E
Rosemead, California (U 338-E) — Cancelling Revised Cal. PUC Sheet No. 60311-E

Schedule TOU-GS-3 — Sheet 5

TIME-OF-USE - GENERAL SERVICE - DEMAND METERED

(Continued)

RATES (Continued)

	Delivery Service								Generation[9]	
	Trans[1]	Distrbtn[2]	NSGC[3]	NDC[4]	PPPC[5]	DWRBC[6]	PUCRF[7]	Total[8]	UG**	DWREC[10]
Option B										
Energy Charge - $/kWh/Meter/Month										
Summer Season - On-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.08819 (I)	0.00000 (I)
Mid-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.05095 (I)	0.00000 (I)
Off-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.03226 (I)	0.00000 (I)
Winter Season - On-Peak	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Mid-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.04662 (I)	0.00000 (I)
Off-Peak	(0.00125) (R)	0.00230 (R)	0.00866 (I)	0.00001 (I)	0.01154 (I)	0.00549 (I)	0.00043 (I)	0.02718 (I)	0.03712 (I)	0.00000 (I)
Customer Charge - $/Meter/Month		446.13 (R)						446.13 (R)		
Demand Charge - $/kW of Billing Demand/Meter/Month										
Facilities Related	4.64 (I)	13.17 (R)						17.81 (I)		
Time Related										
Summer Season - On-Peak		0.00						0.00	17.42 (I)	
Mid-Peak		0.00						0.00	3.43 (I)	
Winter Season - Mid-Peak		0.00						0.00	0.00	
Off-Peak		0.00						0.00	0.00	
Voltage Discount, Demand - $/kW										
Facilities Related										
From 2 kV to 50 kV	0.00	(0.21)						(0.21)		
Above 50 kV but below 220 kV	0.00	(7.11) (I)						(7.11) (I)		
At 220 kV	0.00	(13.17) (I)						(13.17) (I)		
Time Related										
From 2 kV to 50 kV	0.00	0.00						0.00	(0.34) (R)	
Above 50 kV but below 220 kV	0.00	0.00						0.00	(0.93) (R)	
At 220 kV	0.00	0.00						0.00	(0.94) (R)	
Voltage Discount, Energy - $/kWh										
From 2 kV to 50 kV	0.00000	0.00000						0.00000	(0.00121) (R)	
Above 50 kV but below 220 kV	0.00000	0.00000						0.00000	(0.00269) (R)	
At 220 kV	0.00000	0.00000						0.00000	(0.00271) (R)	
Power Factor Adjustment - $/kVAR										
Greater than 50 kV		0.47						0.47		
50 kV or less		0.55						0.55		
California Alternate Rates for Energy Discount - %		100.00*						100.00*		

(Continued)

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APPENDIX H SOUTHERN CALIFORNIA EDISON TOU-GS-2 OPTION

A and B

SOUTHERN CALIFORNIA EDISON
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Southern California Edison		Revised	Cal. PUC Sheet No. 60965-E
Rosemead, California (U 338-E)	Cancelling	Revised	Cal. PUC Sheet No. 60300-E

Schedule TOU-GS-2 — Sheet 3

TIME-OF-USE - GENERAL SERVICE - DEMAND METERED

(Continued)

RATES (Continued)

	Delivery Service								Generation[9]	
	Trans[1]	Distrbtn[2]	NSGC[3]	NDC[4]	PPPC[5]	DWRBC[6]	PUCRF[7]	Total[8]	UG**	DWREC[10]
TOU Pricing - Option A										
Energy Charge - $/kWh/Meter/Month										
Summer Season - On-Peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.31335 (I)	0.00000 (I)
Mid-Peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.08769 (I)	0.00000 (I)
Off-Peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.03086 (I)	0.00000 (I)
Winter Season - Mid-Peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.04757 (I)	0.00000 (I)
Off-Peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.03741 (I)	0.00000 (I)
Customer Charge - $/Meter/Month		220.30 (R)						220.30 (R)		
Facilities Related Demand Charge - $/kW	4.21 (I)	11.27 (R)						15.48 (I)		
Single Phase Service - $/Month		(11.71) (I)						(11.71) (I)		
Voltage Discount, Demand - $/kW										
Facilities Related										
From 2 kV to 50 kV	0.00	(0.20)						(0.20)		
Above 50 kV but below 220 kV	0.00	(6.79) (I)						(6.79) (I)		
At 220 kV	0.00	(11.27) (I)						(11.27) (I)		
Voltage Discount, Energy - $/kWh										
From 2 kV to 50 kV	0.00000	0.00000						0.00000	(0.00165) (R)	
Above 50 kV but below 220 kV	0.00000	0.00000						0.00000	(0.00391) (R)	
At 220 kV	0.00000	0.00000						0.00000	(0.00395) (R)	
California Alternate Rates for Energy Discount - %		100.00*						100.00*		
TOU Optioı $/Meter/Month RTEM		71.01						71.01		
California Climate Credit - $/kWh		(0.00416) (I)						(0.00416) (I)		
TOU Pricing - Option B										
Energy Charge - $/kWh/Meter/Month										
Summer Season - On-Peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.08833 (I)	0.00000 (I)
Mid-Peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.05089 (I)	0.00000 (I)
Off-Peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.03087 (I)	0.00000 (I)
Winter Season - Mid-Peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.04758 (I)	0.00000 (I)
Off-Peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.03742 (I)	0.00000 (I)
Customer Charge - $/Meter/Month		220.30 (R)						220.30 (R)		
Facilities Related Demand Charge - $/kW	4.21 (I)	11.27 (R)						15.48 (I)		
Time Related Demand Charge - Summer Season - $/kW										
On-Peak		0.00						0.00	17.32 (I)	
Mid-Peak		0.00						0.00	3.38 (I)	
Single Phase Service - $/Month		(11.71) (I)						(11.71) (I)		
Voltage Discount, Demand - $/kW										
Facilities Related										
From 2 kV to 50 kV	0.00	(0.20)						(0.20)		
Above 50 kV but below 220 kV	0.00	(6.79) (I)						(6.79) (I)		
At 220 kV	0.00	(11.27) (I)						(11.27) (I)		
Time Related										
From 2 kV to 50 kV	0.00	0.00						0.00	(0.33) (R)	
Above 50 kV but below 220 kV	0.00	0.00						0.00	(0.92) (R)	
At 220 kV	0.00	0.00						0.00	(0.93) (R)	
Voltage Discount, Energy - $/kWh										
From 2 kV to 50 kV	0.00000	0.00000						0.00000	(0.00122) (R)	
Above 50 kV but below 220 kV	0.00000	0.00000						0.00000	(0.00271) (R)	
At 220 kV	0.00000	0.00000						0.00000	(0.00274) (R)	
California Alternate Rates for Energy Discount - %		100.00*						100.00*		
TOU Optioı $/Meter/Month RTEM		71.01						71.01		
California Climate Credit - $/kWh		(0.00416) (I)						(0.00416) (I)		

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APPENDIX I SOUTHERN CALIFORNIA EDISON TOU-GS-2 CPP

SOUTHERN CALIFORNIA EDISON
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Southern California Edison — Revised Cal. PUC Sheet No. 60967-E
Rosemead, California (U 338-E) — Cancelling Revised Cal. PUC Sheet No. 60302-E

Schedule TOU-GS-2 — Sheet 5

TIME-OF-USE - GENERAL SERVICE - DEMAND METERED

(Continued)

RATES (Continued)

	Delivery Service								Generation[9]	
	Trans[1]	Distrbtn[2]	NSGC[3]	NDC[4]	PPPC[5]	DWRBC[6]	PUCRF[7]	Total[8]	UG**	DWREC[10]
Option CPP										
Energy Charge - $/kWh										
Summer Season										
On-Peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.08833 (I)	0.00000 (I)
Mid-peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.05089 (I)	0.00000 (I)
Off-Peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.03087 (I)	0.00000 (I)
Winter Season										
Mid-peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.04758 (I)	0.00000 (I)
Off-Peak	(0.00124) (R)	0.00237 (R)	0.00912 (I)	0.00001 (I)	0.01214 (I)	0.00549 (I)	0.00043 (I)	0.02832 (I)	0.03742 (I)	0.00000 (I)
Customer Charge - $/month		220.30 (R)						220.30 (R)		
Single Phase Service - $/month		(11.71) (I)						(11.71) (I)		
Facilities Related Demand Charge - $/kW	4.21 (I)	11.27 (R)						15.48 (I)		
Time Related Demand Charge - $/kW										
Summer Season										
On-Peak	0.00	0.00						0.00	17.32 (I)	
Mid-Peak	0.00	0.00						0.00	3.38 (I)	
Voltage Discount, Facilities Related Demand - $/kW										
From 2 kV to 50 kV	0.00	(0.20)						(0.20)		
Above 50 kV but below 220 kV	0.00	(6.79) (I)						(6.79) (I)		
At 220 kV	0.00	(11.27) (I)						(11.27) (I)		
Voltage Discount, Time-Related Demand - $/kW										
From 2 kV to 50 kV	0.00	0.00						0.00	(0.33) (R)	
Above 50 kV but below 220 kV	0.00	0.00						0.00	(0.92) (R)	
At 220 kV	0.00	0.00						0.00	(0.93) (R)	
Voltage Discount, Energy - $/kWh										
From 2 kV to 50 kV									(0.00122) (R)	
Above 50 kV but below 220 kV									(0.00271) (R)	
At 220 kV									(0.00274) (R)	
TOU Option Meter Charge - $/month										
TOU-RTEM		71.01						71.01		
CARE Energy Discount - %		100.00*						100.00*		
CPP Event Energy Charge - $/kWh									1.37453	
Summer CPP Non-Event Credit										
On-Peak Demand Credit - $/kW									(10.75)	
Maximum Available Credit - $/kW**										
On-Peak									(19.69) (R)	
Mid-Peak									(3.85) (R)	
California Climate Credit - $/kWh		(0.00416) (I)						(0.00416) (I)		

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REFERENCES

2017 ERCOT System Planning Long-Term Hourly Peak Demand and Energy Forecast (Rep.). (2016, December 14). Retrieved April 27, 2017, from Ercot website: http://www.ercot.com/content/wcm/lists/114580/2017_Long-Term_Hourly_Peak_Demand_and_Energy_Forecast.pdf

Adjangba, S. (2015, March 13). REDUCE YOUR FACILITY'S ELECTRICITY PEAK LOAD & DEMAND CHARGES. Retrieved February 28, 2017, from https://www.linkedin.com/pulse/reduce-your-facilitys-electricity-demand-charges-sam-adjangba

Albadi, M. H., & El-Saadany, E. F. (2007, June). Demand response in electricity markets: An overview. In Power Engineering Society General Meeting, 2007. IEEE (pp. 1-5). IEEE.

Berglund L, Gonzales R, Gagge A. 1990. Predicted human performance decrement from thermal discomfort and ET*. Proceedings of the fifth international conference on indoor air quality and climate, Toronto, Canada, vol 1:215-220.

Blarke, M. B. (2012). Towards an intermittency-friendly energy system: Comparing electric boilers and heat pumps in distributed cogeneration. Applied Energy, 91(1), 349-365.

Calderwood, W. (2016, January). A Surprising Peak Electric Demand Contributor. Retrieved February 28, 2017, from https://buildingenergy.cx-associates.com/a-surprising-peak-electric-demand-contributor

CEN, E. (2007). 15242 Ventilation for buildings-calculation methods for the determination of air flow rates in buildings including infiltration.

Cengiz, M. S., & Mamiş, M. S. (2015). Price-efficiency relationship for photovoltaic systems on a global basis. International Journal of Photoenergy, 2015.

Coincident demand, coincident peak demand, noncoincident peak demand. (n.d.). Retrieved March 01, 2017, from https://www.energyvortex.com/energydictionary/coincident_demand__coincident_peak_demand__noncoincident_peak_demand.html

Crawley, D. B., Pedersen, C. O., Lawrie, L. K., & Winkelmann, F. C. (2000). EnergyPlus: energy simulation program. ASHRAE journal, 42(4), 49.

D.P. Wyon, Indoor environmental effects on productivity. IAQ 96 Paths to better building environments/Keynote address, Y. Kevin. Atlanta, ASHRAE, 1996, pp. 5–15.

Dave Dieziger (2000). Saving Money by Understanding Demand Charges on Your Electric Bill. United States Department of Agriculture Forest Service, Technology & Development Program, 7100 Engineering, 0071-2373–MTDC

De Coninck, R., & Helsen, L. (2013, August). Bottom-up quantification of the flexibility potential of buildings. In Building simulation, 13th international conference of the international building performance simulation association, IBPSA, Aix-les-Bains, France.

De Normalización, C. E. (2008). EN ISO 13790: Energy Performance of Buildings: Calculation of Energy Use for Space Heating and Cooling (ISO 13790: 2008). CEN.

Denholm P, Hand M. Grid flexibility and storage required to achieve very high penetration of variable renewable electricity. EnergyPolicy 2011;39:1817–30.

Djunaedy, E., Van den Wymelenberg, K., Acker, B., & Thimmana, H. (2011). Oversizing of HVAC system: signatures and penalties. Energy and Buildings, 43(2), 468-475.

Djukanovic, R., Wargocki, P., & Fanger, P. O. (2002). Cost-benefit analysis of improved air quality in an office building. Proceedings of Indoor Air, 1, 808-13.

DOE Building Energy Codes Program Commercial Prototype Building Models. http://www.energycodes.gov/development/commercial/90.1_models.;1; Accessed on 2/10/2017.

Dyson, M., & Mandel, J. (2015). The Economics of Demand Flexibility: How "Flexiwatts" Create Quantifiable Value for Customers and the Grid. Rocky Mountain Institute, August.

EBC Annex 67 Energy Flexible Buildings. (n.d.). Retrieved March 01, 2017, from http://www.iea-ebc.org/projects/ongoing-projects/ebc-annex-67/

Energy Design Resources (2013). Integrating Demand Response Capability Into Facility ... (n.d.). Retrieved February 28, 2017, from https://energydesignresources.com/media/17052134/EDR_DesignBriefs_demandresponse.pdf?tracked=true

Energy Department Announces $53 Million to Drive Innovation, Cut Cost of Solar Power. (n.d.). Retrieved April 27, 2017, from https://energy.gov/articles/energy-department-announces-53-million-drive-innovation-cut-cost-solar-power

Energy Information Administration (US). (2012). Annual Energy Review 2011. Government Printing Office.

ELECTRIC SERVICE TARIFF: DEMAND PLUS ENERGY CREDIT RIDER ... (n.d.). Retrieved February 28, 2017, from https://www.georgiapower.com/docs/rates schedules/interruptible/13.00_DPEC.pdf

ELECTRIC SCHEDULE A-10 Sheet 1 MEDIUM GENERAL DEMAND ... (n.d.). Retrieved March 1, 2017, from http://www.pge.com/tariffs/tm2/pdf/ELEC_SCHEDS_A-10.pdf

ELECTRIC SCHEDULE E-19 Sheet 1 MEDIUM GENERAL DEMAND ... (n.d.). Retrieved February 28, 2017, from http://www.bing.com/cr?IG=9CFE3DCD5C7541D9B73BFA8ED904BAB0&CID=04ABF4BA732560723168FE8272146146&rd=1&h=5LNAeYWhOhJa7j1aeATH2VUYkAQ7rSaCu95FpbmD5OQ&v=1&r=http%3a%2f%2fwww.pge.com%2ftariffs%2ftm2%2fpdf%2fELEC_SCHEDS_E-19.pdf&p=DevEx,5061.1

Federspiel CC, Fisk WJ, Price PN, Liu G, Faulkner D, Dibartolemeo DL, Sullivan DP, Lahiff M. Worker performance and ventilation in a call center: analyses of work performance data for registered nurses. Indoor Air Journal vol 14. (2004) Supplement 8: 41-50.

Felts, D., and P. Bailey. (2000). The state of affairs-packaged cooling equipment in California. *Proceedings of the 2000 ACEEE Summer Study on Energy Efficiency in Buildings, Pacific Grove, CA, August 20–25*, Vol. 3, pp. 137–47.

G. B. Dantzig. Linear programming under uncertainty. Management Science, 1:197–206, 1955.

Gentle, J. E., Härdle, W. K., & Mori, Y. (Eds.). (2012). Handbook of computational statistics: concepts and methods. Springer Science & Business Media.

Hansen, S., & Brown, J. (2003). Investment Grade Audit-Making smart energy choices.

Health, wellbeing and productivity. (2014 September). Retrieved February 28, 2017, from http://www.ukgbc.org/campaigns-policy/campaigns/health-wellbeing-and-productivity

Hostick, D., Belzer, D., Hadley, S., Markel, T., Marnay, C., & Kintner-Meyer, M. (2014, July). Projecting Electricity Demand in 2050 (Rep. No. PNNL-23491). Retrieved April 27, 2017, from U.S. Deaprtment of Energy website: http://www.pnnl.gov/main/publications/external/technical_reports/PNNL-23491.pdf

Huber, M., Dimkova, D., & Hamacher, T. (2014). Integration of wind and solar power in Europe: Assessment of flexibility requirements. Energy, 69, 236-246.

Huber M, DimkovaD, Hamacher T. Integration of wind and solar power in Europe: assessment of flexibility requirements. Energy 2014; 69:236–46.

Jacobs, P. (2003). Small HVAC field and survey information. California Energy Commission report, 500-03.

Johansson, C. Mental and perceptual perform-ance in heat. Report D4:1975. Building research council. Sweden. 283 p.

Kim, J. H., Augenbroe, G., & Suh, H. S. (2013). Comparative study of the LEED and ISO-CEN building energy performance rating methods. In 13th conference of international building performance association, France.

Kosonen, R., & Tan, F. (2004). Assessment of productivity loss in air-conditioned buildings using PMV index. Energy and Buildings, 36(10), 987-993.

Lan, L., Wargocki, P., & Lian, Z. (2011). Quantitative measurement of productivity loss due to thermal discomfort. Energy and Buildings, 43(5), 1057-1062.

Lan, L., Wargocki, P., Wyon, D. P., & Lian, Z. (2011). Effects of thermal discomfort in an office on perceived air quality, SBS symptoms, physiological responses, and human performance. Indoor Air, 21(5), 376-390.

Lee, S. H., Zhao, F., & Augenbroe, G. (2013). The use of normative energy calculation beyond building performance rating. Journal of Building performance simulation, 6(4), 282-292.

Link, J., Pepler R. Associated fluctuations in daily temperature, productivity and absenteeism. No 2167 RP-57, ASHRAE Transactions (1970) Vol 76, Part II:326-337.

Lopes, R. A., Chambel, A., Neves, J., Aelenei, D., & Martins, J. (2016). A Literature Review of Methodologies Used to Assess the Energy Flexibility of Buildings. Energy Procedia, 91, 1053-1058.

Masters, G. M. (2013). Renewable and efficient electric power systems. John Wiley & Sons.

Mechri, H. E., Capozzoli, A., & Corrado, V. (2010). USE of the ANOVA Approach for Sensitive Building Energy Design. *Applied Energy, 87*(10), 3073-3083. doi: 10.1016/j.apenergy.2010.04.001

McLain, H. A., Goldenberg, D., Karnitz, M. A., Anderson, S. D., & Ohr, S. Y. (1985). Benefits of replacing residential central air conditioning systems (No. ORNL/CON-113). Oak Ridge National Lab., TN (USA)..

Miessner, C A. (2016, June 01). APS 2016 Rate Review Executive Summary BRIDGE TO THE FUTURE. Retrieved March 01, 2017, from http://docplayer.net/27796316-Aps-2016-rate-review-executive-summary-bridge-to-the-future.html

Minneapolis. (n.d.). Retrieved March 01, 2017, from http://database.aceee.org/city/minneapolis-mn#sthash.H1udZ3Pk.dpuf

Mount, E. 2004. Investment Grade Energy Audit; Making Smart Energy Choices, Sci-Tech News, 58(2), 53f

NARUC 2017: A little less climate and a lot more infrastructure (Feb 2017) http://www.utilitydive.com/news/naruc-2017-a-little-less-climate-and-a-lot-more-infrastructure/436334/

National Grid - Demand (G-2). (n.d.). Retrieved February 28, 2017, from https://www9.nationalgridus.com/masselectric/business/rates/4_g2.asp

Net Metering Axed, Huge Setback for Solar. (2016, December 30). Retrieved March 01, 2017, from http://azbex.com/net-metering-scrapped-huge-setback-for-az-solar/

Nexus, I., Nexus, I. I., Nexus, I., Forecasting, I., Forecasting, I. I., Motion II, B. M. I. B….& Motion IV, B. (1978). Applied time series analysis.

Niemelä R, Hannula M, Rautio S, Reijula K, Railio J. 2002. The effect of indoor air temperature on labour productivity in call centres – a case study. Energy and Buildings. 34: 759-764.

NU Transmission | NU Transmission Projects. (n.d.). Retrieved March 01, 2017, from http://www.transmission-nu.com/residential/projects.asp

Nuytten, T., Claessens, B., Paredis, K., Van Bael, J., & Six, D. (2013). Flexibility of a combined heat and power system with thermal energy storage for district heating. Applied Energy, 104, 583-591.

Palisade Corporation (2017). @Risk; Ithaca, NY. Available from: http://www.palisade.com/risk/

Pepler, R., Warner R. 1968. Temperature and Learning: An experimental study. Paper No 2089. Transactions of ASHRAE annual meeting, Lake Placid, 1967:211-219.

PLM-11 ELECTRIC SERVICE TARIFF: POWER AND LIGHT MEDIUM SCHEDULE ... (n.d.). Retrieved February 28, 2017, from https://www.georgiapower.com/docs/rates-schedules/medium-business/4.00_PLM.pdf

Programs & Rebates. (n.d.). Retrieved March 01, 2017, from https://www.xcelenergy.com/programs_and_rebates

R. Niemela¨, J. Railio, M. Hannula, S. Rautio, K. Reijula, Assessing the effects of indoor environment on productivity, in: Proceedings of the Seventh World Congress, CLIMA 2000, Naples, September 2001.

Renedo CJ, Ortiz A, Man˜ana M, Silio D, Perez S, Study of different cogeneration alternatives for a Spanish hospital Center, Energy and Buildings, 2006, 38:484 – 490.

RS Means Company. (2017). Building construction cost data. RS Means Company.

Ruiz Flores, R., Bertagnolio, S., & Lemort, V. (2012, July). Global sensitivity analysis applied to total energy use in buildings. In *Proceedings of the 2nd International High Performance Buildings Conference*

Ruya, E., & Augenbroe, G. (2016). THE IMPACTS OF HVAC DOWNSIZING ON THERMAL COMFORT HOURS AND ENERGY CONSUMPTION. IBPSA-USA Journal, 6(1).

Sachen, S. (2013, July). Demand Response: Unsung Hero of NY Heat Wave. Retrieved February 28, 2017, from https://www.energyacuity.com/blog/bid/307214/Demand-Response-Unsung-Hero-of-NY-Heat-Wave

Saltelli, A., Tarantola, S., Campolongo, F., Ratto, M., (2004). Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models. John Wiley & Sons, Ltd.

SB 1585 2017 http://www.ilga.gov/legislation/BillStatus.asp?DocNum=1585&GAID=13&DocTypeID=SB&SessionID=88&GA=99

SCE TOU-GS-2 https://www.sce.com/NR/sc3/tm2/pdf/ce329.pdf

Schedule GS-2 - sce.com. (2017). Retrieved February 28, 2017, from https://www.sce.com/NR/sc3/tm2/pdf/ce30-12.pdf

Schedule TOU-GS-3 - sce.com. (2017). Retrieved February 28, 2017, from https://www.sce.com/NR/sc3/tm2/pdf/CE281.pdf

Schwieger, V. (2004, November). Variance-based sensitivity analysis for model evaluation in engineering surveys. In INGEO 2004 and FIG Regional central and Eastern European conference on engineering surveying, Bratislava, Slovakia (pp. 11-13).

Seppanen, O., Fisk, W. J., & Faulkner, D. (2003). Cost benefit analysis of the night-time ventilative cooling in office building. Lawrence Berkeley National Laboratory.

Seppanen, O., Fisk, W. J., & Faulkner, D. (2004). Control of temperature for health and productivity in offices. Lawrence Berkeley National Laboratory.

Seppanen, O., Fisk, W. J., & Lei, Q. H. (2006). Room temperature and productivity in office work. Lawrence Berkeley National Laboratory.

Simmons, B., Tan, M. H., Wu, C. J., & Augenbroe, G. (2015). Determining the cost optimum among a discrete set of building technologies to satisfy stringent energy targets. Artificial Intelligence for Engineering Design, Analysis and Manufacturing, 29(04), 417-427.

Six, D., Desmedt, J., Vahnoudt, D., & Bael, J. V. (2011, June). „Exploring the flexibility potential of residental heat pumps combined with thermal energy storage for smart grids “. In 21th International Conference on Electricity Distribution, Paper (Vol. 442).

Standard, A. S. H. R. A. E. (2004). Standard 55-2004. Thermal environmental conditions for human occupancy, 9-11.

Sun, Y. (2014). Closing the building energy performance gap by improving our predictions (Doctoral dissertation, Georgia Institute of Technology).

Sun, Y., Heo, Y., Tan, M., Xie, H., Jeff Wu, C. F., & Augenbroe, G. (2014). Uncertainty quantification of microclimate variables in building energy models. Journal of Building Performance Simulation, 7(1), 17-32.

Sun, Y., Su, H., Wu, C. J., & Augenbroe, G. (2015). Quantification of model form uncertainty in the calculation of solar diffuse irradiation on inclined surfaces for building energy simulation. Journal of Building Performance Simulation, 8(4), 253-265.

Thomas, P. C., & Moller, S. (2007). HVAC System Size: Getting It Right—Right-Sizing HVAC Systems in Commercial Systems, 2007. Cooperative Research Centre for Construction Innovation, 11.

U.S. – Canada Power System Outage Task Force - PSOTF: Final Report on the Implementation of Task Force Recommendations. (n.d.). Retrieved March 01, 2017, from http://energy.gov/oe/downloads/us-canada-power-system-outage-task-force-final-report-implementation-task-force

U.S. Energy Information Administration, Annual Energy Outlook 2015, Reference Case, Table 8: Electrical supply, disposition, prices, and emissions

U.S. Energy Information Administration - EIA (2016). 2012 Commercial buildings energy consumption survey. United Sates Department of Energy, Ed., ed.

U.S. Energy Information Administration - EIA - Independent Statistics and Analysis. (n.d.). Retrieved February 28, 2017, from http://www.eia.gov/tools/glossary/

Understand your energy statement. (n.d.). Retrieved February 28, 2017, from https://www.pge.com/en_US/business/your-account/your-bill/understand-your-bill/energy-statement/gas-and-electric-statement-page-3.page

Vanhoudta D, Desmedta J. Van Baela J, Robeyn N, Hoes H (2011), An aquifer thermal storage system in a Belgian hospital: Long-term experimental evaluation of energy and cost savings, Energy and Buildings, 2011, 43: 3657 – 3665.

WGBC (2014 September). Health, wellbeing and productivity. (2014 September). Retrieved February 28, 2017, from http://www.ukgbc.org/campaigns-policy/campaigns/health-wellbeing-and-productivity

Willem, H. C. (2006). Thermal and indoor air quality effects on physiological responses, perception and performance of tropically acclimatized people (Doctoral dissertation).

Witterseh, T. 2000. Environmental perception, SBS symptoms and performance of office work under combined exposure to temperature, noise and air pollution. PhD Thesis. International Centre for Indoor Environment and Energy, Department of Mechanical Engineering. Technical University of Denmark

Woradechjumroen, D., Yu, Y., Li, H., Yu, D., & Yang, H. (2014). Analysis of HVAC system oversizing in commercial buildings through field measurements. Energy and Buildings, 69, 131-143.

World Energy Investment Outlook. IEA (2003). Retrieved March 01, 2017, from http://www.worldenergyoutlook.org/media/weowebsite/2008-1994/weo2003.pdf

Zhang, Y., & Augenbroe, G. (2014, September). Right-sizing a residential photovoltaic system under the influence of demand response programs and in the presence of system uncertainties. In Building simulation.